University of Southern Queensland

TACTILE PERCEPTION BY TISSUE FORCE CHARACTERISTICS FOR ROBOTIC RED MEAT CUTTING

A Thesis submitted by

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ABSTRACT

This research investigates an approach to tactile perception for guiding a cutting tool attached to a robotic system processing red meat. Conventional tactile sensing methods, reliant solely on spatial force values, have met with inconsistent results when addressing the complex cutting conditions in red meat processing. The variability inherent in red meat workpieces, coupled with the deformations induced by processing forces, necessitates an innovative machine perception approach to match the adaptability required in red meat processing tasks. This research explores an alternative approach leveraging temporal sensory data to discriminate meat tissues and tissue interfaces in real-time, thereby informing the trajectory of the cutting tool relative to the position of the deforming meat tissues. The strategy correlates unique characteristic force transients in the force data with predefined key cutting events of the task. While the thesis focuses on developing and validating the tactile perception strategy through experimental setups, it does not extend to full deployment in a robotic system. The methodology has been validated through experimentation using a custom-designed test rig including a 6-axis robotic manipulator, 6-axis force sensor, and high-resolution cameras. The results showed high precision in identifying unique force transients in the data and the key cutting moments in the performed task relative to the cutting tissues and tissue interfaces involved, which were consistent across cuts on comparable tissue arrangements. These principles are relevant across trimming and separation operations, where following tissue interfaces that are not visible during the operation is necessary. The forces exerted at the cutting edge of the knife indicate when the knife is approaching an interface, while the orthogonal side forces detect the behaviour of the deformable meat tissues causing the knife to deviate from a predefined cutting path. The results have enabled the proposal of a simplified machine perception strategy for trimming striploin steak by cutting relative to the real-time position of tissues and tissue interfaces. The investigation has produced new understanding and knowledge on guiding cutting in meat along tissue interfaces, using correct interpretation of force feedback to formulate judgment and cutting strategy ready to be executed. The proposed 'skilled robot system' aims to replicate human operator adaptability for various cutting tasks.

CERTIFICATION OF THESIS

I, Basem Adel Ahmed Aly, declare that the PhD Thesis entitled **Tactile perception by tissue force characteristics for robotic red meat cutting** is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes.

This Thesis is the work of Basem Adel Ahmed Aly except where otherwise acknowledged, with the majority of the contribution to the papers presented as a Thesis by Publication undertaken by the student. The work is original and has not previously been submitted for any other award, except where acknowledged.

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STATEMENT OF CONTRIBUTION

I, Basem Adel Ahmed Aly, declare that I have made the majority contribution (more than 50%) to the following papers, upon which this thesis is based.

Paper 1:

Aly, BA, Low, T, Long, D, Baillie, C, & Brett, P 2023, ‘Robotics and sensing technologies in red meat processing: A review’, Trends in Food Science and Technology, 137, 142-155. https://doi.org/10.1016/j.tifs.2023.05.015

Basem Ade Aly: Conceptualisation, Investigation, writing the original draft.
Professor Peter Brett: Conceptualisation, Review & editing.
Dr Tobias Low: Review & editing.
Dr Derek Long: Review & editing.
Professor Craig Bailie: Review & editing.

Paper 2:

Aly, BA, Low, T, Long, D, Baillie, C, & Brett, P 2023, ‘Tactile sensing for tissue discrimination in robotic meat cutting: A feasibility study’, Journal of Food Engineering, 363, 142-155. https://doi.org/10.1016/j.jfoodeng.2023.111754

Basem Ade Aly: Conceptualisation, Investigation, performing experiments, writing the original draft.
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Dr Tobias Low: Review & editing.
Dr Derek Long: Review & editing.
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Aly, BA, Low, T, Long, D & Brett, P 2023, ‘Robotic Fat Trimming: Characterisation Of Red Meat Tissue Structure Using Tactile Perception’, Journal of Food Engineering. (Accepted with revisions)

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CHAPTER 1: INTRODUCTION

1.1. Research aim and objectives

This research aims to produce a simplified cutting strategy for trimming striploin steak by cutting relative to the real-time position of tissues and tissue interfaces. This strategy is based on results from robotic tactile perception and the analysis of unique force transients observed during simple cuts relative to different tissues and their interfaces. The developed cutting strategy contributes to the development of a real-time machine tactile perception technique for automatically guiding a cutting tool attached to a robotic system. This tool operates near internal meat tissue interfaces to perform typical cuts in beef processing operations, similar to the approach used by skilled human operators during manual slicing in abattoirs.

Normally achieved by highly skilled human operators, cutting operations require both the use of visual and tactile senses to plan, anticipate and determine the state of the cut during the process. In this way, the operator can execute cutting trajectories such that certain tissue interfaces are not penetrated to preserve high-value meat mediums, maintain defined thickness of surface layers of fat above muscle tissue interfaces and to produce the desired shape for the product.

Meat deforms in response to applied cutting forces and there are various tissue phenomena encountered when cutting. These are primarily tissue types, tissue interfaces and cavities within tissues. Some of these can offer guidance on cutting trajectories while others should not.

A novel tactile sensing scheme is presented here that identifies with the force characteristics (spatiotemporal) as opposed to spatial force values only. These are used to discriminate cutting conditions amenable to the required cutting path. Temporal variations and signal transients can be interpreted automatically to discriminate the placement of cutting trajectory relative to tissue interfaces. Following this approach, cutting can be performed successfully. The approach is relevant as many industry meat cutting operations are guided relative to tissue interfaces.

The focus of the study is to demonstrate the feasibility of tactile sensing as a perception tool to guide a knife when cutting red meat. The study assesses the accuracy of unique transients in the tactile signal data for discriminating between different tissue types (fat and muscle) and identifying the position when the blade is approaching or crossing the interfaces between them. The study also examines how these tissues deform in response to cutting forces at critical stages of the operation. The insights gained are used to develop a simple cutting strategy for trimming a striploin steak, focusing on cutting relative to the interface between the fat and muscle layers.

To achieve the aim of the study, the following research questions are proposed to guide the stages of the research:

Question 1: What consistent mechanical features in red meat tissues can be reliably detected using tactile perception?

Question 2: How feasible and precise is tactile perception in identifying red meat tissue features and behaviour during cutting?

Question 3: What are the persistent unique transients in the tactile data that discriminate tissues and their interfaces?

Question 4: How can the unique force transients related to the mechanical features of red meat be interpreted to identify key cutting events?

Question 5: Can tactile perception-based techniques inform a control strategy to guide a cutting knife toward an automated cutting system?

Accordingly, the objectives of this work are as follows:

1- Review and evaluate both the state of robotics and automation in red meat and pork cutting and deboning, and the applicability of existing sensing technologies for guiding robotic systems in real-time.
2- Develop a versatile testing rig to identify tissue cutting force characteristics through correlation with tissue presentation within samples and to be ready for further work to guide cutters automatically relative to tissues using the tactile sensing technique.
3- Strategically choose test samples and experimental conditions that allow observations of cutting actions and tissues behaviour while processing.
4- Investigate an approach to identify and discriminate key tactile characteristics of tissues and important structures to guide trajectories relative to meat tissue and tissue interfaces.
5- Formalise an approach to identify and discriminate key tactile characteristics of tissues and important structures to guide trajectories relative to meat tissue and tissue interfaces was achieved.
6- Create a cutting strategy for demonstration to perform a simplified version of cutting a typical marketable product (Striploin trimming).

1.2. Motivation and challenges of integrating robots in red meat processing

The red meat and livestock industry is a significant contributor to the Australian economy. It constitutes 27% of the total agricultural sector with a value add of $13.5 billion from 2020 to 2021 (Meat & Livestock Australia, 2022). The industry revolves around the following animal stock: cows, veal, and buffalo, when slaughtered for beef these form a significant part of the market with sheep and goat forming a smaller contribution. These species are defined in the Australian market as the source of ‘red meat’. Within this industry, the processing industry subsector follows farming as the second largest contributor, adding 23% (or $3.1 billion) to the industry’s total value in terms of GDP. According to Meat & Livestock Australia (Meat & Livestock Australia, 2022), the red meat and livestock industry employs over 400,000 individuals directly or through associated businesses, with the processing sub-sector accounting directly for 31,200 jobs. Furthermore, Australia also has a strong presence on the consumption side, ranking as the world’s seventh-largest beef consumer.

In the red meat global market, Australia stands as a leading exporter. The country ranks as the fourth largest beef and veal exporter after Brazil, India and USA, while it leads the world in sheep meat and goat meat exports (Meat & Livestock Australia, 2022). It has a 3% share of global beef production and around 6.7% of global sheep meat production (Meat & Livestock Australia, 2022). The national and international significance of the industry drives the motivation to take advantage of increasing opportunities in the rising new markets. Improving the processing sector is crucial to maintain competitiveness.

1.2.1. Business challenges

The industry faces numerous challenges related to manual labour in abattoirs. One of the major issues concerns employee-related costs, which are considered one of the highest in the world. This imposes disadvantage in the face of international markets and for consumers where pricing is critical. The disadvantage is increasingly more prominent given that competitors worldwide are rapidly improving product quality. Table 1 shows costs related to the industry in Australia and the other competition. In Australia, labour-related costs account for 85.4% of the total costs per head, while in USA, Brazil and Argentina, it is less than 50 %.

Table 1: Analysis of regulatory and related costs in red meat processing

	Australia		**United States**		**Brazil**		**Argentina**	
Cost category	Cost per head (AU$)	As % of total costs (excl. livestock purchases)	Cost per head (AU$)	As % of total costs (excl. livestock purchases)	Cost per head (AU$)	As % of total costs (excl. livestock purchases)	Cost per head (AU$)	As % of total costs (excl. livestock purchases)
Labour-related costs	$210.54	85.4%	$129.46	44.6%	75.63	43.9%	$88.31	42.9%
Utilities-related costs	$21.62	6.0%	$12.26	4.2%	19.93	11.6%	$13.05	6.3%
Certification-related costs	$7.29	2.0%	$1.49	0.5%	0.52	0.3%	$2.28	1.1%
Total (excl. livestock costs)	$360.62	100.0%	$290.15	100.0%	172.29	100.0%	$205.96	100.0%
Cost per kg HSCW	$1.22		$0.80		0.70		$0.92	

Furthermore, the industry suffers from recruiting and retaining highly skilled operators. In an attempt to solve this problem, the industry has resorted to hiring temporary operators from overseas. This is an expensive solution. Despite these efforts, a 20% shortage in skilled labour remains. An alternative being considered is to increase livestock exports without prior processing. However, this would reduce significant added value by the industry.

Arduous and hazardous conditions within abattoirs result in significant financial losses due to prevalent health-related issues and injuries (Purnell & Grimbsy Institute of Further & Higher Education, 2013). Moreover, direct human contact with the meat can lead to the transfer of foreign bodies, which negatively impacts the quality of the meat and its shelf life (Purnell & Grimbsy Institute of Further & Higher Education, 2013). A typical deboning room operates at a fast pace, leaving little time for workers to perform their assigned tasks accurately. This high-pressure environment often leads to mistakes.

These factors, coupled with increasing demand for red meat and the competitive pressure from the emergence of plant-based protein alternatives, underline the urgent need for increased productivity. Consequently, the future of the industry is predicted to be rooted in automation and robotics-based technology. Implementing such technologies will mitigate the current issues and propel the industry forward, ensuring it remains competitive on the global stage.

1.2.2. Operational Challenges in Implementing Robotics for Meat Processing

Successful implementation of robotics with any degree of autonomy in an industrial process hinges on two factors where adaptive machine autonomy needs further improvement to control response: the characteristics and properties of the product being processed and the nature of the task itself.

Red meat as a material is characterised by inconsistent presentation and unpredictable behaviour. The majority of red meat tissues comprise muscles and fats, both of which possess plastic and visco-elastic properties (Choi et al., 2013). This results in the carcass undergoing deformation. The shape of the carcass can change due to external forces such as gravitational force depending on the way the carcass is held and positioned, and during the cutting process when cutting forces are applied. The deformation of red meat tissues is further influenced by the type of tissues being cut, their distribution and the direction of the cut relative to the direction of the tissues (Nabil et al., 2015). Moreover, the dimensions of red meat carcasses, especially beef, can vary considerably. The structural consistency of these carcasses is non-uniform and can differ significantly between animals due to uncontrollable variables such as breed, gender, environmental conditions, and feeding practices (Schumacher et al., 2022; Toldrá, 2006).

The variable and dynamic nature of red meat tissue, combined with product specificity, renders adopting conventional automation systems based on pre-operative perception unsuited to industry needs. The current most common sensing approaches, such as CT scanning and DEXA can only define fixed pre-operation cutting trajectories without the ability to respond to real-time variations. The technologies use ‘Snap shot’, pre-process measurements to determine spatial values for guiding machines, without taking the response of the meat subjected to varying gravitational or applied processing loads.

Conventional techniques for holding and handling products fail when applied to red meat carcasses. Deviations during processing, whether due to tissue deformation and deflection influenced by gravity or applied processing forces, the slippery texture of the tissues, can cause the cutting tool to deviate from its designated path. This will culminate in product damage and a consequent reduction in yield.

For traditional automation of the past to be effective, every aspect of the process needs to be predictable and to minimise variations requiring real-time adaptation by processing machinery. A common characteristic emerges when looking at the three leading industries indicated in Figure 1. These have seamlessly integrated automation technologies for processing: their target products are rigid and exhibit consistent process behaviour, with minimal variation in presentation. This stands on the opposite side of the product spectrum to processing natural products and red meat.

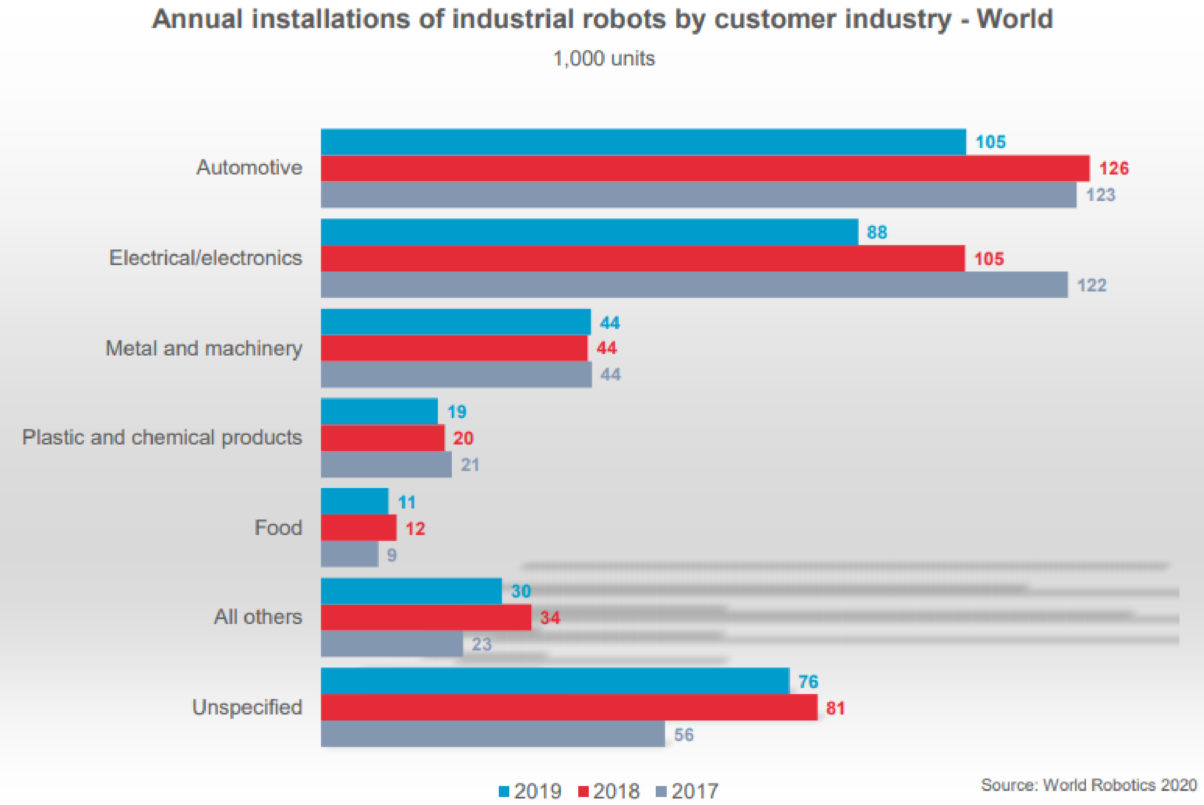

Figure 1: Robotics in Various Industries (IFR International Federation of Robotics, 2021)

Another further operational consideration lies in the selection of the appropriate cutting tool. One cutting tool cannot suffice for all red meat cutting tasks. The choice is influenced by the nature of the cut, its location, and the tissues involved. Certain cuts are obscured, nestled within the carcass or beneath other tissues, necessitating specialised tools to access these areas. Static knives of different shapes and pneumatic cutters are suitable for softer tissues in trimming and slicing operations. Static and electrically powered saws are used to cut through bones (Figure 2).

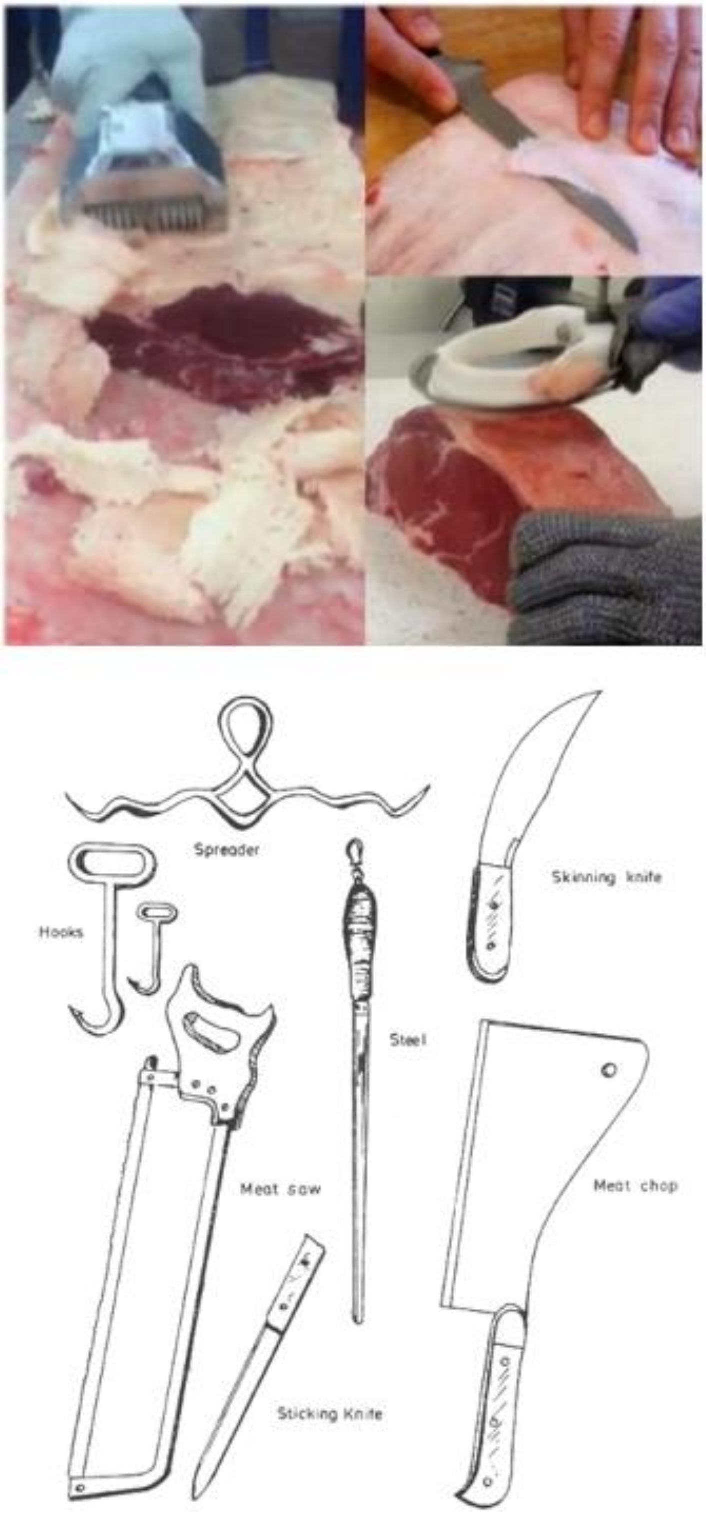

Figure 2: Manual cutting tools

Market specifications are another factor, representing customer requirements and contrasts between markets. The presentation and specification of the end product must be appealing and precise, making the cutting process very delicate and can be damaged by inappropriate handling. According to UNECE Standard (UNECE, 2016), two of the minimum requirements related to food safety that have to be met in a cut are:

- The product must be intact and presentable. The product's final shape must appeal to the market (customers). Table 2 shows typical fat thickness specifications in one particular meat product.
- The product must be free of broken bones. The cutting tool must not cut through the bones and follow the interface between bones and muscles. For maximum profit, the meat attached to bones has to be minimal.

Table 2: Fat limitations in a cut (UNECE, 2016)

Fat thickness code	Category
0	Not specified
1	Peeled, denuded, surface membrane removed
2	Peeled, denuded
3	Practically free (75% lean/seam surface removed)
4	3 mm maximum fat thickness or as specified
5	6 mm maximum fat thickness or as specified
6	13 mm maximum fat thickness or as specified
7	25 mm maximum fat thickness or as specified
8	Chemical lean specified
9	Other

For a robotic system to be considered viable and investment-worthy, Meat and Livestock Australia (MLA) has developed criteria that have to be met (Ruberg, 2021). This includes exceeding the accuracy of manual operation for the same cut, improving the yield in the final product, and replacing the work of at least five labourers per unit installation.

1.3. Solution rationale

Humans can interpret complex information from sensory perception and respond appropriately with measured strategy in real-time to enable the required result when 'crafting' a product. They are capable of discriminating between different mediums, learning and anticipating unexpected occurrences, making decisions driven by past experiences and present data, and adapting and solving new and unforeseen problems. In contrast, in principle, industrial robots are general-purpose programmable machines that could outperform human operators if programmed to execute actions from a correct interpretation of appropriately presented sensory information. These robots demonstrate high accuracy in performing fully specified tasks, have endurance and consistency in operations, respond quickly to any sudden changes in the environment, and can work in extreme working conditions. The combination of human-like perception capabilities to achieve superhuman qualities in machines, given machine attributes of persistence in performing cuts, no fatigue, and repeatability, could potentially yield a system that unifies the best of both worlds by leveraging the attributes of both robotic systems and human operators.

The increasing capabilities of robotics and their role in ‘Industry 4.0’ highlight the vast potential of the technology. However, a fundamental understanding of critical process functions, such as the response of interaction with tools deployed in natural workpieces, needs to be understood to address and position the machine advantage.

Red meat cutting is based on the physical interaction between the cutting tool and the carcass. Despite the non-uniformity and unpredictability of red meat carcasses, consistent materialistic features across all carcasses can serve as the base for a robust control strategy to guide a separation task. Every red meat cut comprises three distinct mediums: bones, fats, and muscles, with connective tissues in between, as illustrated in Figure 4. This makes all the cuts generated from a carcass can be divided into four groups, delineated by the mediums involved:

- Muscle from muscle cut.
- Muscle from bone cut (deboning).
- Fat from muscle (that includes the trimming processes).
- Bone from bone (joints).

Figure 4: Types of Mediums: Fats, Bones, and Muscles (Left to Right) (Jacob, 2018)

Cuts are executed by following the interfaces between these mediums or relative to them. Observing manual operators in deboning rooms provides insights into the complexities of red meat tissue separation and the skills required to accomplish it. Operators apply knowledge from experience about the target task to determine the correct cutting path relative to the features of the carcass and the specifications of the target market. These operators depend on their visual and haptic senses to control the cutting tool with real-time interaction with the state of the workpiece and apply judgment to ensure the knife follows the correct cutting path and achieves the desired outcome. However, their primary reliance lies in their sense of touch, given that much of the cutting occurs inside the carcass and between tissues in areas not visible to the eye.

An example of a cut can be demonstrated in Figure 5. The presented cut is crafted from a lamb forequarter. It is done by removing the foreshank, Humerus and Scapular bones following the seams between the overlying and underlying muscles, leaving the undercut attached (UNECE, 2016). The operator starts by marking the interface line between the shoulder and rib cage, then follows the rib cage bone interface all the way until the shoulder falls.

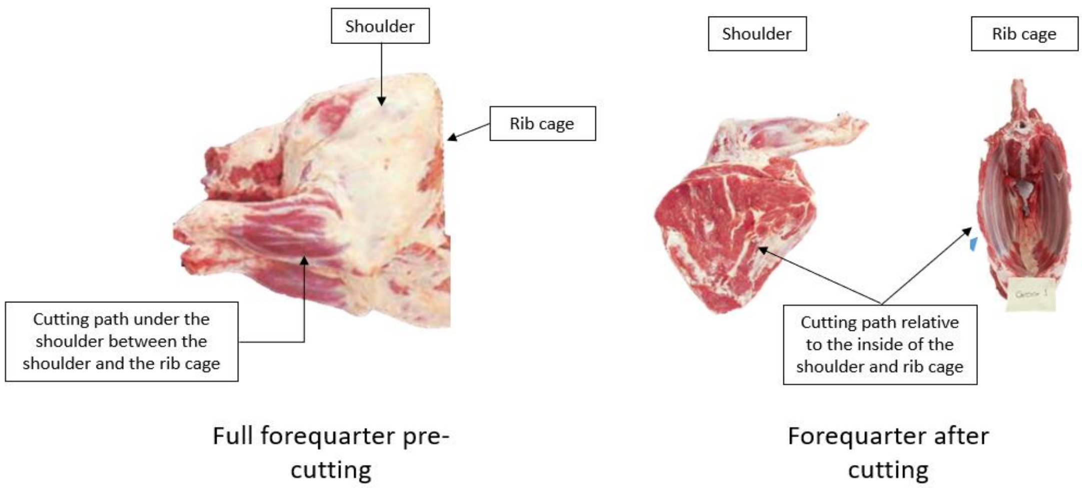

Figure 5: Full shoulder pre-cut and after-cut (UNECE, 2016)

These findings indicate that a similarly functioning robotic system is required for handling such dynamic material. A hybrid system, combining the capabilities of visual and tactile perception, would essentially mimic the techniques of skilled human operators. This integrated approach would offer a versatile solution capable of managing the intricate task of processing highly variable and deformable natural products, such as red meat. This approach presents a viable strategy to navigate the challenges posed by the irregular nature of these products.

1.3.1. Tactile perception as a solution

Tactile perception based technology is the provision of information through physical interaction with the surrounding environment. The technology goal is to detect the mechanical properties or response of the operating medium through force and torque feedback. The data obtained from contacting different objects could be informative if the force transients are observed carefully and interpreted correctly. In red meat processing, tactile perception is an under-researched area, even though the essence of the procedure rests on the physical interaction between the cutting tool and the carcass. Recent literature reveals that efforts to utilise tactile perception in guiding a knife along complex cutting paths have been largely unsuccessful. A significant reason for this is the conventional approach of viewing tactile data merely as numerical values. However, in a natural environment such as that of red meat, where the tissues are constantly changing, tactile data must be perceived differently.

Robotics technology in the medical field and surgical procedures has utilised tactile data presented by force and torque sensors to develop real-time informative sensing techniques with great accuracy. Brett et al.(Taylor, 2008) developed and tested a successful technique to guide medical drilling, utilising both force and torque feedback from the tip of the drill. This same technique was employed for needle insertions, guided by the force feedback from the tip of the needle (Peter N Brett et al., 1997; Maurin et al., 2004). The technique emphasised identifying the unique transients and patterns in the tactile data rather than just viewing them as values. These unique transients correlate with crucial moments during surgery, providing invaluable insights to discriminate different mediums and to anticipate key events during procedures.

Inspired by the technique’s success in the dexterous medical field, there’s potential to adapt it for cutting red meat tissues. Learning from these medical applications emphasises importance of the reactive transients in the tactile feedback as an identification tool for discriminating features and states in red meat tissues during operations in near real-time. This approach enables an appropriate response to conditions by taking account of typical tissue behaviour that can be used to control during critical events. When cutting red meat, the response could be through oscillating the knife to cut through an interface or tilting and rotating the knife to counter deformation and restore the desired cut path.

1.4. Thesis layout

Each chapter contributes towards the investigation to identify an approach to tactile perception for cutting red meat tissues. This will be covered in the following chapters by fulfilling the objectives mentioned in Section 1.1. It should be noted that the chapters with follow-ups are structured this way because they are published papers with word limit constraints, which could not accommodate the additional follow-up information.

Chapter 2.1: This chapter discusses complexities associated with integrating robotics into the red meat processing industry. A review of the latest advancements in automation systems for cutting and deboning red meat and pork is provided with a specific focus on sensing technologies and perception techniques of these systems. Furthermore, this chapter assesses the suitability of common sensing technologies for real-time guidance, a crucial requirement for successful robotics implementation to process dynamic red meat tissues. Emerging assistive technologies in the red meat industry are also presented. These are potential alternative solutions before full automation of red meat cutting tasks.

Chapter 2.2: This chapter expands on the review of the innovative approaches to utilising tactile perception in robotics, focusing on applications that process materials with properties similar to red meat.

Chapter 3: This chapter details the practical approach used to investigate tactile perception in red meat cutting. It explains the rationale for the experimental design, which is aimed at addressing the research questions and achieving the overall research goal. The chapter provides an overview of the experiments conducted throughout the thesis, detailing the aims, procedures, and approaches for gathering and analysing data in each experiment. It also discusses all the variables influencing robotic cutting and how they are controlled across the experiments. Finally, the chapter introduces a theoretical model that shows the types of forces applied to the knife during cutting and the distribution of these forces, including a free-body diagram illustrating the forces acting on the knife.

Chapter 4, Section 1: This section of Chapter 4 outlines a systematic approach aimed at investigating the viability of tactile perception in discriminating tissues and tissue interfaces, and identifying key cutting events while executing simple cuts on different tissue types within prepared test samples. Tactile data is represented through force measurements from a force sensor attached to a knife mounted on a robotic manipulator. The feasibility of the technology is demonstrated by identifying similarities in force patterns and recognising distinctive transients associated with different cutting events.

Chapter 4, Section 2: Addressing one of the primary challenges encountered in the experiment described in Chapter 4.1, this chapter investigates how the accuracy of capturing unique force transients during the cutting process is affected by the cutting depth of the knife.

Chapter 5, Section 1: This section of Chapter 5 extends the results and observations from the experimental work of Chapter 4 to characterise a more practical application: striploin chop trimming using force feedback. It explores the effectiveness of using both the leading force component on the tip of the knife and the orthogonal force components on the sides of the knife simultaneously to discriminate the proximity of the knife relative to interfaces. In addition, the correlation between the lateral force component and the contour of the tissue interface the knife follows. The results obtained from this experiment were used to develop a simplified cutting strategy for effectively trimming a layer of fat from the top of a striploin chop relative to the interface between the fat layer and the muscle tissue.

Chapter 5, Section 2: A continuation of Section 5.1, presenting further experimental runs to enhance the findings by analysing additional cutting paths, key cutting events, and the relative unique force transients recorded by the force sensor.

Chapter 6: This chapter discusses results and observations from the experimental work within the broader spectrum of automated red meat processing. The chapter aims to synthesise these findings, highlighting the significant advancements made in tactile perception technology and its application in robotic meat cutting.

Chapter 7: Conclusion of the research outcomes.

CHAPTER 2

2.1. LITERATURE REVIEW - PAPER 1- ROBOTICS AND SENSING TECHNOLOGIES IN RED MEAT PROCESSING: A REVIEW

2.1.1. Introduction

This paper provides a comprehensive review of the advancements and challenges in integrating robotics and sensing technologies in red meat cutting. It highlights the need for automation in an industry characterised by physically and mentally demanding tasks, particularly in the deboning rooms. We discuss the complexities involved in automating meat processing, stemming from the diverse nature of red meat carcasses and their unpredictable deformable behaviour during processing. The paper also examines state-of-the-art technological solutions, focusing on sensing technologies for precision cutting and methods for processing sensory information.

2.1.2. Published paper

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Robotics and sensing technologies in red meat processing: A review

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ABSTRACT

Background: The red meat processing industry has a harsh work environment where tasks performed in abattoirs are physically and mentally demanding. In addition, the high financial costs associated with employing skilled labour, the shortage of such workers, and the rise in worldwide meat consumption, there has been a growing push towards integrating automation as a potential solution for the industry.

Scope and approach: This paper describes the complexities of implementing robotics technology in red meat processing. The complexity when processing deformable natural meat mediums is significantly sensitive to the variations of workpieces caused by mechanical properties, physical shape and the position of tissues. These differences hinder conventional robotic systems from succeeding.

Experimental and commercial robotic systems in red meat processing are shown to perform cutting tasks in the deboning room, whose systems capabilities are limited by executing cuts requiring little to no adaptability during the process. The review shows that X-ray, optical probes, and ultrasonic are the most effective sensing technologies in determining the cutting trajectories prior to the task. Some experimental systems utilised tactile sensing to follow more complex cutting paths but have not yet produced a commercially viable product. The evaluation of these sensing technologies' applicability to guide a robotic system in real-time is critical to tackling more complex cuts.

Key findings and conclusions: A combination of preoperative scanning and real-time perception for adaptive control is recommended to automate tasks in red meat cutting. Also, it is recommended that to fully automate the meat cutting process, a gradual approach should be taken by shifting abattoirs by first utilising assistive technologies such as cobots, exoskeletons augmented reality, and virtual reality.

1. Introduction

Red meat[1] processing is an industry with an arduous work environment. The nature of the tasks performed in the abattoirs is physically and mentally demanding. In response to these challenges, the industry is moving towards integrating automation technologies to improve workplace safety and productivity. Automation in the paper pertains to industrial automation, which aims to control a physical process automatically without human intervention. This category of automation utilises physical machines and control systems to automate diverse tasks within an industrial process. On the other hand, robotics refers to the use of intricate mechatronic systems, also referred to as robots, that come equipped with electronics, sensors, actuators, and software to perform specific tasks with varying degrees of autonomy (Haidegger, 2020). Purnell et al. have summed up the reasons that justify why red meat processing is ideal for incorporating automation in the deboning room (Purnell & Grimsby Institute of Further & Higher Education, 2013):

- The near-freezing temperature of the work environment leads to serious health problems in the long term.
- The repetitive nature of the tasks performed in the deboning room causes mental and physical fatigue.
- Operators 'deboners' in the deboning room work in close proximity to sharp tools, which can result in injuries leading to absenteeism, compensation claims, and decreased production consistency.

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[1] Red meat in this paper refers to beef and lamb as they represent the majority of the processing sector in Australia, any other type of meat is mentioned by name such as pig meat industry.

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- The presence of human operators in the deboning room can cause foreign bodies and microorganisms to be transferred into the meat, necessitating a significant budget to maintain high levels of hygiene.

Moreover, the learning curve for different cuts is high. A typical deboning room has a chain speed where every deboner has limited time to perform the assigned task of cutting. That makes red meat processing unattractive for recruiting a new workforce and an unforgiving learning environment for the new workers.

In recent years, Australia has been among the leading countries globally for exporting red meat, including beef, sheepmeat, and goatmeat. In 2019, Australia was the second-largest beef and veal meat exporter and the largest sheepmeat exporter (Meat & Livestock Australia, 2020). The red meat industry plays a crucial role in Australia's economy, providing employment to approximately 434,000 individuals from different regions and remote areas, either directly within the industry or through associated businesses (Meat & Livestock Australia, 2020; Ruberg, 2021). Given the industry's importance, Australia is motivated to capitalise on emerging opportunities.

The red meat industry faces a significant challenge regarding processing costs due to labour, with Australia experiencing a substantial difference in employee-related costs compared to other leading red meat exporting nations (Ruberg, 2021; SG Heilbron Economic & & Policy Consulting, 2018). For instance, the employee-related costs for beef account for 57.7% ($210.54) per head of a total cost of $360.62, while for sheep and lamb, it is 55.2% ($22.4) of $40.67 (SG Heilbron Economic & & Policy Consulting, 2018). With other countries improving the quality of their products to match Australian products, Australia is competing in the global market with a cost disadvantage, especially with price-sensitive consumers (Ruberg, 2021). Statistics show that the Australian labour-related cost rate is 1.6 times greater than the USA, 2.8 times greater than Brazil, and 2.4 times greater than Argentina (SG Heilbron Economic & & Policy Consulting, 2018). There is also pressure to efficiently increase red meat production to meet the market demand as the annual consumption of protein increases (Ruberg, 2021). Robotics is a key technology that can contribute to the required production increase and reduce labour costs to maintain competitiveness.

Transforming live animals into marketable products involves numerous operations within the abattoir. While the sequence of these operations may vary slightly between species and countries, Kim et al. provide a general outline of the typical slaughterhouse line sequence (Kim, Kwon, Kim, Seol, & Cho, 2023):

1) Stunning
2) Bleeding
3) Skinning or dehairing
4) Evisceration
5) Carcass cutting (the focus of this paper)

All stages of red meat processing are crucial to the quality of the final product and could greatly benefit from automation. However, this paper focuses on carcass cutting, where the most intricate and valuable cuts are produced in the challenging environment of the cold deboning rooms. The paper demonstrates some of the complexities with respect to red meat as a natural material, and their implications for operational aspects such as the manipulation and gripping of carcasses. Shortcomings of the existing automatic robotic systems and their sensing technology in handling red meat products in deboning rooms are presented. Specifically, this review examines their ability to adapt to the non-uniform cutting paths and the deformable nature of red meat tissues.

The paper indicates that the solution lies in a perception technology to guide a robot that mimics human perception capabilities by discriminating events and states to inform machine control functions in real-time. Most of the commercial solutions reviewed utilised non-reactive perception methods to guide a blade during cutting, using preoperative scans that dictate the cutting path for the manipulator. However, this approach was limited to cutting tasks where little to no adaptation was required during the cut. This paper also showcases some assistive technologies that have the potential for short-term implementation, while paving the way towards fully automating the industry.

The structure of this paper is as follows: Section 2 discusses the technical and operational challenges associated with integrating robotics to cut red meat. Section 3 describes the search methodology used during the literature review process. Section 4 presents the current state-of-the-art attempts to automate pork and red meat cutting and reviews the primary sensing technologies used in these systems. Finally, Section 5 highlights various assistive technologies that could be implemented in the deboning room.

2. Complexities of red meat automation

Successfully integrating robotic systems within any industry heavily depends on the tasks involved in the process and product characteristics. Adapting robotics to skillfully 'craft' red meat is complex. Current conventional robotics technology is not yet ready to process such mediums and has various aspects that still need to be explored. Highly automated industries, such as the automotive, electrical/electronics, and metal/machinery sectors, have a commonality in their product characteristics, enabling them to leverage automation to a greater extent (IFR International Federation of Robotics, 2021). These industries have the following attributes in common:

- **Consistency:** the input product has known coordinates and measurements before being handled. Features and properties of the products are the same in terms of structure and size, reducing the need for adaptation to variations.
- **Rigidity:** the product's behaviour while processed is predictable, allowing the reliance on preoperative data and simulation models to be robust to drive the control system.

Conversely, processing natural products, including red meat, is complicated due to inconsistencies that vary from the non-homogenous structure, the variable dimension of the product, and the unpredictable responses when handled. Additionally, the presentation and specifications of the product must be precise and visually appealing, making the cutting process delicate, as any inappropriate handling can cause damage (Purnell & Grimbsy Institute of Further & Higher Education, 2013). Moreover, market specifications are an essential consideration as they represent the changing demands of customers across different locations (UNECE, 2004). These specifications define the pre-operation cutting plan and determine the performance score of the automated system. All these challenges must be adequately addressed to have a successfully working robotic system in meat processing that can assist the industry in achieving maximum profitability through improving product quality and minimising losses. The following sections will address various factors contributing to the complexities involved in processing red meat, which are largely attributed to the meat's characteristics and how they affect various aspects of handling.

2.1. Factors related to workpiece presentation

The first parameters required to be known for a manipulating robotic system are the size and dimensions of its input. This is particularly challenging when it comes to red meat products, which are non-uniform and vary in size. The input dimensions are impossible to anticipate due to factors such as the chemical composition of the food fed to the animal and the variability between species, gender, age and geographical origin of the animal (Schumacher, DelCurto-Wyffels, Thomson, & Boles, 2022; Toldrá & Leo, 2006). Even within cuts of the same type and size, internal features such as tissue distribution and measurements can vary significantly. Border et al. observed such discrepancy when dissecting striploin pieces of roughly the same length. The fat thickness varied randomly between 2 and 75 mm. from the interface with the muscles (Border, Brett, & Baillie, 2019; Khodabandehloo, 2018).

Moreover, the location and trajectory of the cutting path and the type of cutting mediums contribute to the complexity of the task. These factors affect the product's state when inputted into the system, the type of cutting tool required, and the manipulation technique needed. For example, unexposed cutting paths covered by tissues are more challenging to follow than exposed ones and require special handling and unique cutting tools capable of reaching the cutting areas. The trajectory of the path could be as simple as a straight line of cut or following the complex bone profile around the joints. The types of mediums of separation add to the complications of the cut. It is harder to differentiate between similar tissues visually or through haptics, and so performing a cut between similar tissues is more difficult than distinctly different ones.

2.2. *Factors related to workpiece behaviour*

The nonlinear mechanical properties and composite structure of red meat tissues cause the non-uniform behaviour of the products in the abattoirs (Merenkova, Zinina, Khayrullin, Bychkova, & Moskvina, 2020). Red meat is mainly made up of deformable visco-elastic tissues: muscles and fats (Choi, Zhang, Fuhlbrigge, Watson, & Tallian, 2013). The stiffness of these tissues varies within the same specimen and across them. Fat tissue is composed of fat cells connected by connective tissues. The combinations of the fatty acids that create the fat cells decide the stiffness of the fat (MLA & AMPC, 2008). There are six different main types of fatty acids in cattle and sheep with different Carbon chain lengths and thus different mechanical properties (MLA & AMPC, 2008; Schumacher et al., 2022). Similar to the carcass's size, environment, breed of the beast and diet are all factors that affect the composition of the fatty acids and the distribution of the fats across the carcass (Schumacher et al., 2022). There are four types of fats in the carcass (Sheridan et al., 1994):

- Intramuscular fat is located within the meat muscle.
- Intermuscular fat is located between muscles.
- Subcutaneous fat or back fat is located between meat muscles and skin. They are distributed as lumps of fat layers on the top of the muscles, with connective tissues between these layers (Lonergan, Topel, & Marple, 2019).
- Visceral fats are located around the internal organs.

Skeletal muscles are the majority of the animal's soft tissues. It represents the edible meat and the profitable part of the carcass. The muscles have a complex composition with a combination of the following components (See Fig. 1) (Megías, Molist, & Pombal, 2023):

- The connective tissue that covers each muscle is called Endomysiuma and is made of collagen.
- A bundle of muscle fibres is grouped to form larger muscle masses and is covered with another type of connective tissue called Perimysium. These bundles are also called "grain" of meat, which have direction—made of collagen.
- Epimysium or silver skin is the outer layer of connective tissue that wraps the whole muscle. Unlike the previous connective tissue, it is made of a heavier type of protein called elastin.
- A percentage of intramuscular fat exists between the muscle bundles (marbling).

Fig. 1. Muscles' internal structure (Megías et al., 2023).

In some cases, bones must be retained inside the product. This makes the bone, a more rigid and heavier medium, an important consideration while cutting. Joints between bone tissues are connected through ligaments, which is another form of elastin-based connective tissue. Also, bones are connected to meat muscles through connective tissue known as tendons (Megias et al., 2023).

The presence of two or more different mediums within a product can result in non-uniform rheological properties during handling and processing. The viscoelastic properties of these tissues can cause phenomena such as tissue relaxation over time due to variations in gravitational force vectors and inertial forces, changes in structure as mass portions are removed, and transient deformation induced by cutting tool forces during disassembly. An experiment conducted to identify the rheological parameters of beef round muscles showed that the meat exhibited different deformational behaviours when a load was applied in three directions relative to the direction of meat fibres (Nabil, Belhassen-Chedli, & Grigore, 2015).

2.3. *Factors related to the setup and the process of cutting*

a) Gripping and manipulation

Manipulating a carcass involves holding it at certain positions against the blade or changing its orientation relative to the cutting tool. How the workpiece is presented to the cutting tool is crucial for following the target interface efficiently. Conventional methods of handling rigid materials are not suitable for processing red meat due to the aforementioned factors (Choi et al., 2013). As a result, innovative manipulation techniques inspired by manual processing were developed, which can vary for each cut. The two common experimental manipulation techniques are (Khodabandehloo, 2022):

- In the first technique, the robot holds the cutting tool while the workpiece is fixed in a known position and orientation (Scott Technology Limited, 2013).
- In the second technique, the robot manipulates and holds the workpiece against a fixed blade for cutting (Maunsell & Scott Technology Ltd, 2018).

Properly securing a highly deformable object of various structures like red meat carcasses and fixing it against the blade in both techniques is crucial to achieving the desired results. Any movement during the process could cause deviations from the cutting trajectory, leading to yield loss or unsatisfactory damaged products. Bader and Rahimifard have categorised the properties of materials and their impact on automation (Bader & Rahimifard, 2020). According to their classification, the influence of natural materials that possess slippery surfaces, irregular shapes and sizes, and non or semi-rigid properties on automation are:

- Higher probability of grip loss or slip-induced grip loss.
- Damage resulting from pressure.

The most common gripping technologies in the red meat industry are hooks and clamp grippers with adjustable holding force powered by either electrical motors or pneumatically (Ross, Korostynska, Cordova-Lopez, & Mason, 2022). Takács et al. conducted a state-of-the-art review to assess the feasibility of various gripping concepts and designs in the red meat industry (Takács, Mason, Christensen, & Haidegger, 2020). One of the types examined was prosthetic hands, which were deemed too intricate and inefficient to be implemented in the industry. Other grippers presented with under-actuated fingers, which can mould themselves to the shape of the object they are holding, making them ideal for grasping meat and deformable items. However, there are concerns with the technology, such as the low payload capacity and the cleanliness aspect of food safety, as it is constructed using 3D printing material. Other unilateral grippers including vacuum, magnetic, gel, and penetrating grippers are not explored heavily in the red meat industry. Ross et al. reviewed these options and found that magnetic and gel grippers are not suitable for use with meat due to incompatibility, while penetrating grippers negatively affect the final product's appearance and can cause damage (Ross et al., 2022). The only viable option is the vacuum gripper, which utilises air suction or vacuum to hold objects from one side without causing damage, being simple, cheap, and easy to clean. However, vacuum grippers have relatively higher yet limited holding forces, which is a major concern when it comes to handling heavy payloads of red meat primary cuts. Therefore, the author suggested that more research is needed to develop new design configurations and test their suitability in the industry.

b) Cutting tools

Cutting tools depend on the type of cut required and the types of tissues involved. Static knives of different shapes and pneumatic cutters are suitable for softer tissues in trimming and slicing operations, whilst static and electrically powered saws are used to cut through bones. All the current cutting tools perform the cut through direct contact with the workpiece. Contact cutting requires constant sterilisation to prevent contamination from spreading and periodic blade sharpening to ensure clean cuts. To prevent such issues, other technologies that provide contactless cutting are being researched and tested (Foster & Machinery Automation & Robotics Pty Ltd, 2011; Khodabandehloo, 2022), including water jets, ultrasonic cutting, laser beams, and plasma. The cutting tool impacts important cutting parameters and procedures, such as the position of the workpiece, the manipulation technique and the cutting velocity.

2.4. *Health and safety considerations*

The deployment of robotics in abattoirs with any level of automation requires various health and safety considerations that must be taken into account. However, since integrating the technology into the red meat sector is a new concept, the available standards can be overly restrictive and which prohibit the industry from exploring and implementing these technologies (Romanov, Korostynska, Lekang, & Mason, 2022).

One of the primary concerns is ensuring the hygienic aspect of meat processing, as foreign bodies such as bacteria, fungi and metal or plastic fragments can contaminate the products, and the damp environment in abattoirs can promote rust on the end-effector (Kim et al., 2023). The equipment is recommended to be specially designed to comply with criteria set by specialised standards such as the International Organisation for Standardisation (ISO) 14159 for machine design (International Organization for Standardization, 2002). This includes using food-grade materials for manufacturing closed machines that are easy to clean and disinfect without the risk of getting rusty or causing any chemical reactions. It is also necessary to implement periodic cleaning protocols to clean the manipulators immediately between each cut to prevent cross-contamination and at the end of each working shift. An example of a comprehensive standard that can be applied is ISO 22000, which provides a framework for managing food safety (International Organization for Standardization, 2018).

Another important consideration when implementing robots in the red meat sector is safety, as working with robots at any level of automation can be potentially dangerous. Takács et al. conducted a review of the standards and regulations that can be used as guidelines and found that ISO10218:2011 is the most relevant for the technology (Takács et al., 2023). This standard provides guidelines and requirements for the safe design of machinery, including robots, presenting protective measures, foreseeable hazards, and suggestions to eliminate or reduce the risks associated with them. Moreover, the effect of failure in the control system must be examined to ensure safety. Lastly, hazards associated with specific robot applications must be assessed and mitigated to prevent accidents and ensure food safety. Effective measures must be implemented to address these safety issues and ensure the safe and efficient operation of robotics in the red meat industry.

3. Research method

A structured search methodology was used to comprehensively analyse commercially available and experimental automation systems for meat processing, specifically for primal cutting and deboning tasks. The search focused on systems that automatically measure the carcass with a clearly described perception technology and then transfer it for cutting automatically without human involvement. To collect the potential published results, several databases were searched, including Science Direct, Scopus, JSTOR, Web of Science and Google scholar, using the following keywords (excluding patents):

- "Automation in meat processing" OR
- "Meat processing robots" OR
- "Robots in abattoirs" OR
- "Artificial intelligence in abattoirs" OR
- "Automation in lamb deboning" OR
- "Robotics in lamb deboning" OR
- "Automation in red meat deboning" OR
- "Robotics in red meat deboning" OR
- "Pig slaughter automation" OR
- "Robotic pig slaughter" OR

Due to the initial search yielding only a small number of results, a subsequent search was conducted using certain keywords from more specific elements of automation systems, such as the sensing technologies utilised or specific tasks performed within the deboning room, such as fat trimming or shoulder deboning. In addition to academic publications, the review also included industry reports from organisations such as the Australian Red Meat Corporation (AMPC) and Meat and Livestock Australia and the manuals of products from major automation companies such as Frontmatec, Marel, and SCOTT Automation. Technologies that set important milestones towards implementing automation in the industry, such as Cobots, virtual reality, and augmented reality, were also included in the review.

It's important to note that the research excluded all solutions from industries with rigid products or products vastly different from red meat, such as poultry and fish. Using this structured methodology and search strategy, the review aimed to provide a comprehensive analysis of the current state of commercially available and experimental automation systems for meat processing, specifically in primal cutting and deboning tasks, while identifying potential research gaps and future directions for the field.

The Technology Readiness Level (TRL) is a metric that gauges the maturity level of a technology or system. The TRL scale ranges from 1 to 9, with 1 indicating the lowest level of maturity and 9 being the highest. When a system is assigned a TRL of 9, it means that it is a fully developed, proven technology that is ready for commercial deployment. The TRL assigned to each system in the meat industry is based on several factors, including the level of technological advancement, the degree of system testing and validation, and the readiness for commercial deployment.

For instance, the AGOL-800 and other commercially available systems have a TRL of 9 because they have been extensively tested and validated in commercial applications. On the other hand, the experimental systems have a TRL ranging from 5 to 7, depending on the level of information available on the stage of the system. RoBUTCHER has the highest TRL among the experimental systems, which is likely to be

Table 1
Automation systems in the meat industry.

Industry	System	Task	Availability	Technology Readiness Level (TRL)	Sensing Technology
Pork	RoBUTCHER	Primal cutting	Experimental	7	computed tomography (CT) data + real-time 3D imagery + electromagnetic spectroscopies
	AGOL-800	primal cutting	Commercial	9	X-ray technology + Vision camera
	AMBL 1100	Pork middle section deboning	Commercial	9	3D vision camera
	Chine bone saw CBCL-100	Chine bone deboning	Commercial	9	3D vision camera
	Automatic Rib Puller ARP15	Ribs removing	Commercial	9	3D vision camera
	Robotic Belly Trimmer	Pork belly trimmer	Commercial	9	3D vision camera
	Automatic Loin Trimmer ALTD-450	Pork loin trimmer	Commercial	9	Ultrasonic sensor and imaging measurements
	Automatic Loin Trimmer ALTL-1100	Pork loin trimmer	Commercial	9	Optical probe
	Auto Trimmer Model AT21-620	Pork butt trimmer	Commercial	9	Optical probe
	HAMDAS-RX	Pork leg deboning	Commercial	9	X-ray image system
	WANDAS-RX	Pork shoulder deboning	Commercial	9	X-ray image system
	SRDViand robotic cell	Pork leg deboning	Experimental		Force sensor
Lamb	X-Ray Primal System	Lamb primal cuts	Commercial	9	X-ray image system
	Middle System	Middle part portioning (the spinal cord and lamb flaps are removed, and the loin is separated from the racks)	Commercial	9	X-ray image system
	Forequarter System	Forequarter portioning (tip the knuckle, remove the brisket bone, the shank and the neck, and split the shoulder)	Commercial	9	3D vision camera
	Hindquarter System	Split the two legs from the femur bone	Experimental	6	Force sensor
	Lamb Chops Trimmer	Trim the fats from lamb chops	Experimental	4	Vision gauge + CCD camera
Beef	Robotic Beed Rib Cutting	Cut across the ribs	Commercial	9	X-ray image system + 3D scanner + Colour camera
	SRDViand robotic cell	Carcass quartering	Experimental	5	Force sensor + Structured light source and a camera
	ARMS robotic cell	Separation of round and shank beef muscles	Experimental	5	Force sensor + Structured light source and a camera

around 7. The system has been tested in laboratory and pilot settings and has shown promising results. However, further testing and validation are necessary before it can be widely deployed in commercial applications.

In contrast, the TRL of the lamb hindquarter system is estimated to be 6. The system has undergone testing with engineering-scale models or prototypes in a relevant environment. Other systems, such as the SRDViand robotic cell and ARMS robotic cell, have a TRL of 5. These systems have been tested in laboratory and pilot settings, and promising results have been achieved, but further testing and validation are necessary before they can be widely deployed in commercial applications.

Finally, the lamb chops trimmer has a TRL of 4. The system has undergone design, development, and lab testing of technological components. The results indicate that the applicable component/process performance targets may be attainable based on projected or modelled systems. Table 1 provides an overview of the reviewed systems, their availability, TRL, and the perception technology used to guide the cutting blade through the task.

4. Technology review: automation in the meat industry

A general architecture of a control system for automated meat processing capable of producing successful products can be envisaged to have the subsystems shown in Fig. 2 (Border, Koodabandehloo, & Brett, 2019). The three subsystems that have different designs in an automatic robotic system also describe the three stages in which a deboner forms an approach to making complex cuts:

- o **Perception:** the deboner observes the overall shape of the workpiece and feels the different mediums using a mix of visual and tactile senses.
- o **Judgement:** they compare the current state of the cut with the final product shape requirement obtained from training and experience.
- o **Execution:** they translate the information into action using proper manipulation techniques and cutting tools.

This section will showcase the commercially available and experimental systems for automating meat processing, focusing on tasks in the carcass cutting process (primary cutting, deboning, trimming). The review will cover the systems' availability, which perception technologies are used to guide the cutting blade, and the adaptability of the systems to the ever-changing presentation and the random behaviour of red meat tissues during the cutting process. As the technology in red meat processing is still in its infancy, we will include automation systems in adjacent industries, such as the pork industry.

4.1. Automation in the pork processing industry

Pork meat processing, which shares similarities with the red meat industry, has found the most success in implementing automation in the industry. In the experimental domain, RoBUTCHER is a European-funded project to develop autonomous robotic cells called meat factory cell (MFC) (Mason et al., 2021). MFC is a concept to replace traditional linear production systems with cell-based ones. The conventional process in abattoirs typically involves sequential steps starting with slaughter, followed by dehairing, evisceration, splitting the carcass into halves, and finally disassembling each half into primary and secondary cuts after chilling. However, the MFC concept proposes rearranging some tasks so that the autonomous cells receive the carcasses directly after dehairing for hot boning of the primals, followed by internal organs removal (Sødring et al., 2022). According to Mason et al., the system comprises two robotic arms, one designated for manipulation and grasping tasks, and the other for cutting. Meanwhile, the carcass handling unit (CHU) supports and holds the carcass during the process (Mason et al., 2021).

The system is capable of adapting to the variations between the different carcasses using a combination of detailed computed tomography (CT) data, real-time 3D imagery, and human-expert cutting data for neural network training toward cutting trajectory planning. The visual data provided by an RGB-D camera aims to identify the carcass's parts and key attributes, feeding this information into a machine-learning algorithm to determine the best gripping location and cutting paths (de Medeiros Esper et al., 2022; Mason et al., 2021). At the same time, sensing techniques to guide a smart knife were explored to detect physical changes within the meat in areas where visual sensing devices are ineffective, such as electrical impedance measurements, force sensing, optical methods, spectroscopic measurements, and electromagnetic wave-based sensing (Alex Mason, Dmytro Romanov et al., 2022). The researchers concluded that only two of these technologies, optical and electromagnetic spectroscopies, are suitable for further development in meat automation. Additional research was conducted, which involved the use of EM spectroscopy to guide a smart knife. The results showed promising performance with only minor errors observed in contact and depth detection (Mason, Romanov, Cordova-Lopez, & Korostynska, 2022). The concept of the MFC delved into several aspects of autonomous robotics and presented many innovative technologies and techniques that can be adopted in red meat.

Commercially, Frontmatec, one of the biggest meat processing automation companies, has developed a range of successful automated solutions for pork cutting, fat removal and trimming. AGOL-800 is a

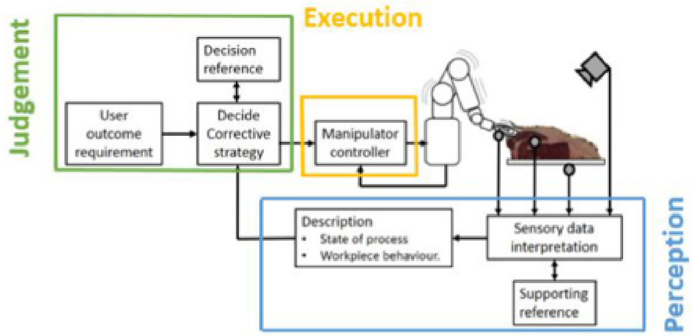

Fig. 2. Control system for automated meat processing (Border, Brett, & Baillie, 2019).

system designed for primal cutting to divide half of the pork carcass into three sections: leg, middle, and fore-end. The system employs X-ray technology, specifically the pubic bone detector, for measuring the carcass (Frontmatec, 2021c). Additionally, the system appears to utilise vision cameras for detecting the orientation and position of the carcass, as observed in the system's demonstration video (Frontmatec, n.d.). Marel and E + V Technology have also developed primal cutting systems, but limited information is available on these systems. However, both systems appear to utilise vision perception to register the position of the carcass and determine the cutting trajectory (Kim et al., 2023; Marel, 2023a).

For further disassembly processing, AMBL 1100 is a versatile system that divides the middle section of the pork into belly and loin, and subsequently debones the loin. This system employs 3D vision cameras, which is demonstrated in the description of the automatic chine bone saw CBCL-100 (Frontmatec, 2022). Frontmatec offers other automated systems for more intricate cuts of the midsection. An example is the Automatic Rib Puller ARP15, which deploys a robotic arm with a specialised cutting instrument (Frontmatec, 2019). The robotic arm is programmed to move along the contours of the ribs, utilising camera images and machine learning algorithms to create a digital model of the pork carcass and accurately identify the location of the ribs (Frontmatec, n.d). Once located, the machine makes precise cuts to remove the ribs from the surrounding tissue. The robotic belly trimmer is another system designed to perform highly precise trimming of pork belly, specifically targeting the teat and backside areas (Frontmatec, 2020). The system incorporates a vision system and data from over 300,000 measurements to create a 3D model, which is used to determine the shape of the belly. The system then utilises two 6-axis robots, each equipped with water jet cutters, to carry out the trimming process.

For fat trimming, ALTD-450 is an automatic trimmer where each piece is scanned using an ultrasonic sensor and imaging measurements to create a 3D profile of the product and detect the muscles/fat interface placement (Frontmatec, 2021a). Then, the piece rests flat on the fat side and is fixed on a conveyor using a pressure wheel to go through the trimming unit. The system uses piano-like blades, which can be adjusted separately to match the required amount of fat to be trimmed from each loin segment. The end product of the system is a loin covered with a uniformly distributed layer of fat. According to Khodabandehloo et al., the system failed to perform the same task for beef loin trimming (Khodabandehloo, 2018). There are other similar systems to trim and remove pork fats, such as ALTL-1100 (Frontmatic) and Auto trimmer model AT21-620 developed by Marel (Frontmatec, 2021b; Marel, n.d.).

HAMDAS-RX and WANDAS-RX are commercially available systems introduced by Mayekaya company for pork shoulder and leg deboning (MYCOM Global, 2020). The systems rely on X-ray vision to identify the path to cut the connective tissues before stripping the muscles from the bone (de Medeiros Esper, From, & Mason, 2021; MAYEKAWA MFG, 2016; MYCOM Global, 2020). These systems have an added feature to help the knife follow the bone surface. A mechanical structure with two springs fixed on the sides of the cutting knife is integrated to allow more freedom of movement laterally for the cutting knife, to avoid getting caught in the narrow areas of the bone (MAYEKAWA MFG, 2016; MYCOM Global, 2020; Toyoshima, Umino, Matsumoto, Goto, & Kimura, 2016).

While the pork carcass shares structural similarities with beef and lamb, pork tissues contain a greater proportion of unsaturated fatty acids that have more fluid characteristics than the saturated fatty acids present in red meat tissues (Kauffman, 2001; Valsta, Tapanainen, & Männistö, 2005; Wood et al., 2008). As a result, trimming systems that rely on preoperative scanning and pushing cuts against adjustable blades are unsuitable for red meat due to its greater deformability, which necessitates constant adaptation of the cutting trajectory during the trimming process. Similarly, deboning techniques are only feasible for pork, due to its softer tissue properties, which facilitate the separation of muscles from bones after a path is cut between them. In addition to that and from observation, pork exhibits a relatively uniform anatomical structure, making it simpler to design effective machines and systems for meat processing tasks. These unique characteristics and properties have enabled the development of various solutions specifically tailored for pork processing automation.

4.2. Automation in the lamb processing industry

Technologies with the ability to measure the internal structure of materials have been the focus of research in the field of automation in red meat as an ideal enabler for control systems. One of the promising technologies to guide an automatic robotic system is Dual-energy X-ray absorptiometry (DEXA). Coupled with 3D scanning cameras, SCOTT Automation has developed and commercialised an automatic lamb deboning room. Analysing the online video published by SCOTT Automation, the system shows that the room is divided into an x-ray cutting system, a primal cutting system, a forequarter cutting system, a middle cutting system, and a hindquarter cutting system (Scott Technology Limited, 2013). The DEXA device scans each lamb carcass to determine the skeletal characteristics (Green, Bryan, & Greenleaf Enterprise, 2014). The system uses the data to identify trajectories that provide precise cut and dissection for each carcass and then send those trajectories down the stream to the subsequent systems (Fig. 3).

The carcass is then moved to the primal cutting system to be split into three main parts: forequarter, middle, and hindquarter (de Medeiros Esper et al., 2021; Green et al., 2014). In the forequarter system, the forequarter part is gripped by a robotic arm and scanned via a 3D vision camera to create a model that identifies the cutting surfaces. The robotic arm uses a fixed saw band to tip the knuckle, remove the brisket bone, the shank and the neck, and split the shoulder through the surfaces calculated by the 3D image (de Medeiros Esper et al., 2021; P.Green et al., 2014; Starling & Robotic Technologies Limited, 2011). In the middle system, the spinal cord and lamb flaps are removed, and the loin is separated from the racks. In the hindquarter system, the two legs are split from the femur bone using a force sensor (de Medeiros Esper et al., 2021; Scott Technology Limited, 2013).

The primal, forequarter and middle systems perform straight line cuts that do not require much cutting adaptability and manipulation if the cutting trajectory and angle are determined correctly. Fig. 4 (a) shows the primal system's outcome as an example of what these types of cuts look like. It can be noticed that the cutting areas are straight lines adjacent to certain structural features in the carcass.

The demonstration video shows a hindquarter cutting system, however it is not commercially available on the company website due to the shortcoming in yield produced in the final product (Maunsell & Scott Technology Ltd, 2018; Ruberg, 2021). The hindquarter cut requires dexterity and accurate manipulation of the cutting tool to cut around the complex profile shape of bone joints connecting the leg with the aitch bone. The knowledge and understanding of the interpretation of force information were insufficient to be used efficiently at this level of complex manipulation. The bone profile of the aitch bone to be followed for this cut can be shown in Fig. 4 (b). Meat and Livestock Australia (MLA) partnered with Mayekawa Global company to have a subsequent attempt at developing the system with no system available to date (Maunsell & Scott Technology Ltd, 2018).

Purnell et al. carried out research to develop a low-cost experimental system for trimming a high-value piece of lamb (lamb chops) (Purnell & Brown, 2004). In their attempt, the authors took advantage of the small size of each individual piece and the deformability of tissues. Instead of following a non-uniform cutting path in a typical piece of lamb chop, a movable segmented wall applies pressure to deform the fat so that the cutting path becomes straightforward and easier to follow. This technique is common in manual operations. It resembles a deboner who applies pressure with one hand and uses the other to move the knife parallel to the interface between the muscles and fat leaving the desired fat height above the muscles.

Fig. 3. Output of DEXA preoperative scan (Green et al., 2014). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

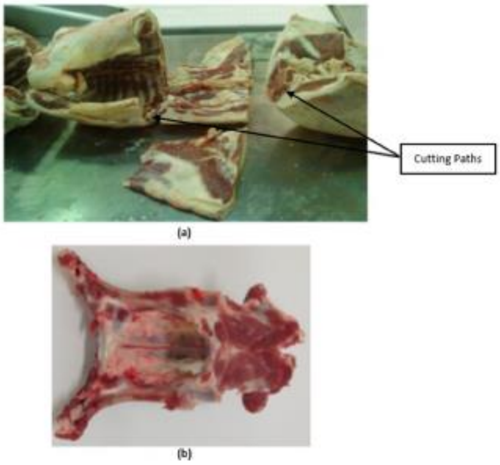

Fig. 4. a) Lamb primal cuts are produced by performing straight cuts (Green et al., 2014), b) The ununiform bone profile for the hindquarter is the cutting path (Maunsell & Scott Technology Ltd, 2018). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

In the machine, the lamb chops were positioned against an adjustable wall. That is combined with ten visual gauges fixed at the hinges of the moving elements of the wall to detect the interface between fat and muscles using the contrast in pixels intensity. In addition, a charged-coupled device (CCD) camera was mounted above the workpiece to provide images of the chop sides. While the system showed slight improvements over manual trimming, some unexpected occurrences, such as blood spots, abnormal chop colouration, and unique anatomy, caused systematic errors in identifying the interface and calculating the cutting path.

4.3. Automation in the beef processing industry

Similar to lamb, automation has been achieved in very few tasks inside the abattoir for beef processing. An automatic robotic system was developed by Scott Automation for rib scribing (Scott Technology Limited, 2022). It uses a circular saw attached to the end of a manipulator to perform two straight-line cuts across the rib. The cutting path information is provided by a combination of X-ray (DEXA) and a colour camera relative to the bones' structure.

As a part of the SRDViand project, a different perception technique to guide the cutting process had to be researched. Whilst all visual technologies showing the carcass's internal structure are expensive and cameras cannot capture the internal cutting paths, tactile perception using force feedback was the test target (Guire, Sabourin, Gogu, & Lemoine, 2010; Subrin, Alric, Sabourin, & Gogu, 2011). The idea was to program the robot to perform accurate anatomical cuts for ham deboning using force control and adapt to changes in real-time. Similar to the lamb hindquarter deboning system, the outcome did not fulfil the final product market specifications and required a deeper knowledge of tactile perception and further system development.

Within the frame of the same project, a strategy was suggested utilising vision and force simultaneously to perform a cut that requires less manipulation; the Z cut for beef carcass quartering (Guire et al., 2010). The process involved the separation of the hindquarter and forequarter. It used the rib cage as a reference to guide the cutting tool. Preoperative visual data using light image was used to obtain the spinal column profile, the four reference points (A, B, C, D), and the spatial position/orientation of the cutting tool relative to them. The system detected the topography of the carcass using a structured light source and a camera (Mosnier, Berry, & Ait-Aider, 2009). The camera captured the light and extracted the carcass's features from it (Mosnier et al., 2009). Tactile perception presented in force feedback was used in real-time to update the cutting tool trajectory to follow the rib cage with the aid of a system to count the number of ribs being cut while locating the position of the knife accordingly. The steps to perform the cut are:

1) The visual data is used to position the knife at starting point A.
2) Follow the 13th rib with a constant force level (machining function).
3) Use the counting system to cut through the rib cage from points B to C.
4) Move the cutting blade in a direction from C to D until a certain force level is detected sensing (assembly functioning), and the blade cuts through the spinal column marking the end of the cut.

More advanced techniques incorporating material modelling and hybrid tactile/vision perception were researched and developed as part of project ARMS, which specialised in robotising muscle separation of meat cutting. Since manipulating the meat to have more control over its behaviour is not a viable solution, especially for sizable pieces, more attention was given to predicting the workpieces' behaviour via modelling and simulation. The models' task is to anticipate the changes in the cutting medium, while the active perception technique provides a real-time update of the process' current state. In reality, it is impossible to accurately model the behaviour of a viscoelastic material like meat considering all the variables mentioned in the previous section while feeding the outcome into a real-time control loop (Cotin, Delingette, & Ayache, 2000). Thus, a solution was suggested to use simpler models as an indication of the behaviour rather than an attempt at accurate prediction.

Nabil et al. investigated several approaches to model and simulate the approximate behaviour of red meat (Nabil et al., 2015). Updated versions of the mass-spring model (MSM) and tensor mass model (TMM) showed promising results when used to represent realistic tissue motion and physical interaction with the cutting tool while maintaining minimal computational time (Han, Wang, Liu, Chen, & Zhang, 2020; Nabil et al., 2015). The models were simulated to reproduce the muscles separation process between round and shank with three different approaches to describe the anatomical cutting (Nabil et al., 2015):

- The model tears the muscles if the applied pulling force exceeds a threshold that varies with the actual thickness of the aponeurosis.
- The model removes the aponeurosis facing the knife's blade as long as sufficient effort is applied (position-based).
- The model cuts through the spring simulating the aponeurosis when the calculated internal force between the nodes exceeds the value of the experimental force modulus.

Furthermore, a visual-based algorithm was presented to detect the aponeurosis's trajectory by calculating the path's curvature features. The experimental rig shown in Fig. 5 was developed as an extension of the previous work to put some of the strategies above into testing (Long, Khalil, & Martinet, 2014b). The pulling robot holds one side of the workpiece, and a camera is attached to the cutting robot above the knife.

The cutting model used in this simulation focused on the local behaviour around the cutting trajectory, simplifying the modelling of the two main muscles to reduce computational time. The cutting medium was represented by a series of spring-damper systems (mass-spring model) spread between the two main muscles. This step achieved positional cutting conditions for each node of the cutting medium. It is important to acknowledge that there is a significant body of research on tissue modeling and behavior. However, the models discussed in this section are specifically those used in the context of the reviewed robotic systems.

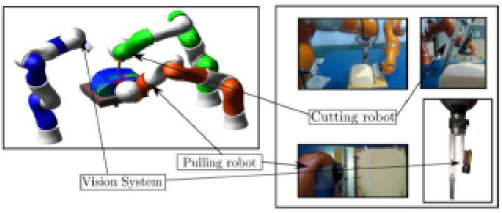

Fig. 5. Experimental rig for beef round muscles separation (Long et al., 2014b).

The camera identified the cutting line location and updated the trajectory with the changes due to the applied forces. The system used the cutting conditions from the simulation to ensure that the knife was cutting through the intermediate interface while avoiding the meat on both sides. Simultaneously, the pulling robot uses force feedback to open the cutting path in front of the blade. Stretching the cutting interface is a common manipulation technique practised by human operators in the deboning room. The method reduces the force needed to cut by stretching the connective tissues between the muscles to assist the knife in following the natural seam.

Despite the effort applied to adapt to the meat deformation changes and the improvement in following the sinew between the muscles, the vision system required to focus on a small area around the cutting blade, and the total cutting path had to be acquired and marked offline before the process. Also, unexpected resistive forces prevented the robot from cutting the whole path length during the cut. In the following stage of the experimental work, a force controller was integrated to detect the accumulation of forces and slicing movement was performed to reduce them. This strategy was tested on foam for validation and is yet to be tested in meat-cutting applications in future work (Long, Khalil, & Martinet, 2014a).

4.4. Perception technologies in the automated systems

Humans can understand complex information from sensory perception and respond appropriately with measured strategy in real-time to enable the required result when crafting a product. This section suggests and discusses that the solution for the industry lies in producing a system that can discriminate between the mediums in a human-like way and utilise the machine's consistency in performing cuts with no fatigue.

Observation of operators cutting in deboning rooms shows knowledge, experience, judgment, and inspiration are being applied in real-time to the changing conditions of perception of behaviour and state of the workpiece (Khodabandehloo, 2022; Purnell & Grimbsy Institute of Further & Higher Education, 2013). Perception is targeted to the task's parameters using multiple sensory information simultaneously. Cutting control is applied with real-time interaction to produce a successful outcome.

Since perceiving the correct information is the key to performing the cut successfully, it is important to highlight the two types of perception that deboners rely on (Khodabandehloo, 2022):

- **Visual perception**: to determine the location of the cutting trajectory, follow the cutting path of some external cuts and identify and react to the apparent behaviour of the workpiece.
- **Tactile perception**: to distinguish between the different mediums within the workpiece, follow the interfaces between tissues and readjust the cutting path to react to any obstacles.

It is evident when referring to Table 1 that visual data is the most prevalent method for perceiving information from the carcass. This can be achieved through different types of cameras for obtaining direct images or through optical probes or X-ray-based technologies to generate images using tissue properties. As established in previous sections, for an automatic robotic system to successfully guide a cutting tool along an appropriate trajectory, it requires to be equipped with real-time data perception capabilities and the ability to adapt to any changes that may occur during the task. This involves a combination of suitable sensing technology and a capable manipulator equipped with the proper cutters working in tandem. In this section, we will assess the applicability of the driving sensing technologies of the systems mentioned earlier in the section to perceive real-time data on the inner state of the carcass. These sensing technologies include vision cameras, X-ray sensing technologies, ultrasonic, optical probes and tactile sensing.

4.4.1. Vision cameras

Vision cameras of various types are essential in recognising the external attributes of a carcass, aiding in the acquisition of its initial measurements and determining key features crucial for gripping and manipulation.They also serve to guide a cutting tool for making shallow cuts or for instances where the internal state of the carcass is not necessary for the cutting process. In their experimental work, Han et al. demonstrated vision-based cutting control for deformable objects (Han et al., 2020). Their proposed approach involved using a vision system to capture surface images of the object and track its contour. Control signals were then generated to adjust the cutting path based on the tracked contour, leading to accurate and efficient cutting. The method's effectiveness was validated through experiments on deformable objects such as sponges, artificial tissues, chicken breasts, and pork liver. However, the technique showed drawbacks due to the need for calibration and the limitation of requiring a clear and unobstructed view of the object, which may not be possible in a real-world abattoir environment.

4.4.2. X-ray sensing technologies

In the case of X-ray technologies, the varying densities of the tissues are used to produce images by detecting the different degrees of attenuation of the X-rays (Delgado-Pando, Allen, Troy, & McDonnell, 2021). Then, a cutting trajectory is generated based on the various features in the carcass, resulting in a two-dimensional image. This technology includes DEXA and CT scanning. The implementation of DEXA technology involves significant expenses, including the installation cost, space requirements, and the need for periodic calibration to verify measurements using a CT scanner, which is also expensive to implement and use. (Australian Government Department of Agriculture, 2019; Jacob & Calnan, 2018). Additionally, this technique has been found to be inadequate when it comes to more complex forms of cutting, such as fat trimming, as it cannot locate subsurface features in three dimensions (Cook et al., 2017).

4.4.3. Ultrasonic

Ultrasonic sensing is another imaging technique to capture the internal structure of an object. This method operates on the principle that tissues of varying densities have different acoustic properties, allowing for the identification of different layers of tissue or objects (Pathak, Singh, & Sanjay, 2011). Ultrasonic devices have two modes of operation: A-mode and B-mode. A-mode is a graph that shows tissue information as a function of depth, while B-mode provides real-time ultrasound images by representing reflected signal amplitude as pixels (Pathak et al., 2011). However, the success of this technology in providing real-time guidance for robotic systems in the red meat industry is challenged by several factors. Specialised ultrasonic device designs are necessary to accommodate the non-uniform shape of carcasses for each specific cut. The placement and orientation of the sensor in relation to the carcass can significantly influence the measurements. The abattoir environment presents various hazards that may disrupt measurement accuracy. Moreover, temperature and water content in the environment can also affect the accuracy of measurements, while the presence of air pockets inside the carcass can lead to measurement inaccuracies (Border, Brett, & Baillie, 2019).

4.4.4. Optical probes

Optical probes are utilised for gauging the physical and chemical properties of diverse materials by analysing their responses to light, including absorbance, reflectance, and backscatter (Delgado-Pando et al., 2021; Prieto, Pawluczyk, Dugan, & Aalhus, 2017). The most commonly used type of optical probe in the meat industry is NIR spectroscopy, which is simple, cost-effective, and robust for preoperative scanning. Its effectiveness has been demonstrated in commercial pork loin trimming systems where it accurately measures fat depth (Frontmatec, 2021b; Marel, 2023b). To obtain measurements, optical diodes are inserted into the fat via a needle-like probe or device. For preoperative scanning of pork products, a single insertion at the product's centre and averaging the data is sufficient, as the fat variation is less compared to that in red meat counterparts. However, utilising optical probes in real-time applications would require numerous readings, necessitating multiple probe insertions into and across the carcass, which may potentially damage the product (Border, Brett, & Baillie, 2019). Also, using it to guide a cutting tool in real-time may lack speed and robustness, but adding artificial intelligence (AI) could aid in decision-making and data analysis to improve its effectiveness (Alex Mason, Dmytro Romanov et al., 2022).

4.4.5. Tactile sensing

Research has shown that the human sense of touch is superior to vision at processing materials' properties, deflection, and details (Luo, Bimbo, Dahiya, & Liu, 2017). Tactile force perception provides force information through physical interaction with the surrounding environment. The technology goal is to detect the mechanical properties or response of the operating medium through force and torque feedback (Luo et al., 2017). The data obtained from contacting different objects could be informative if the force transients are observed carefully and interpreted correctly.

Red meat cutting relies heavily on the physical interaction with the meat workpiece through the cutting blade. Recent research and industrial reports suggest that there is a lack of understanding when it comes to implementing real-time tactile sensing for accurately following the cut path. This deficiency is apparent in the inability to use the technology to guide cutting tools in performing intricate cuts in some of the robotic systems. This is due to the numerous factors that need to be taken into account when relying on haptic technology, such as the direction of the muscle grain, the water content in the tissues, the impact of temperature on meat stiffness, and the non-uniformity of the medium (Border, Brett, & Baillie, 2019).

Many distinct advantages of tactile sensing need more research and investigation. Dario P. et al. demonstrated that understanding and interpreting the parameters related to physical contact with the surrounding environment is the key to complicated sensory techniques capable of adaptively interacting with their surroundings (Duchemin, Dombre, Pierrot, & Poignet, 2003). To adapt to the unexpected behaviour of red meat-compliant tissues, a real-time sensing technique is needed for registering the cutting tools to their unique internal features (Taylor, 2008). The medical field has utilised force and torque sensors to develop real-time informative sensing techniques with micro-level accuracy. This is presented by a method invented and applied by Brett et al. to guide a medical drill through human tissues by force and torque feedback from the drill bit. The proper interpretation of the unique transients of force and torque, regardless of the values, provides information to anticipate conditions on the cutting path and to locate with precision the burr of the drill relative to tissue interfaces. The method divided the trajectory of the drill into four main events to discriminate and control critical stages in the process. Fig. 6 shows how the force and torque vary with tissue depth throughout the drilling process.

The reported method for discriminating tissues and tissue structure offers possibilities for cutting meat. In a similar manner, guiding a knife through red meat tissues to perform a cut requires discrimination between the unique features of the cutting mediums. Developing techniques to perform this discrimination requires a fundamental understanding of critical process events and methods to detect these events so that the system can react to the prominent conditions in real-time. Although tactile sensing is not yet ready for implementation in the meat processing industry and requires further research and

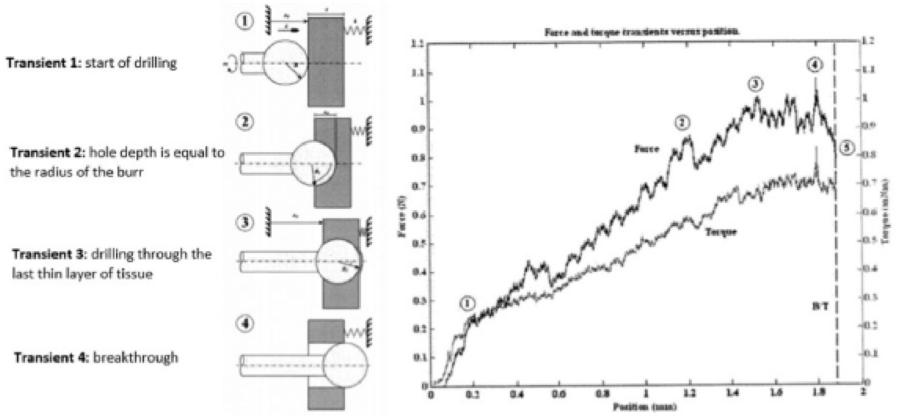

Fig. 6. Force transients during the drilling process (Taylor, 2008).

investigation, this does not diminish its potential as a technology.

5. Assistive technologies

Although automation is perceived to be the saviour of the industry, it is crucial to retain the skillset of workers, particularly with the current shortage of skilled labour. While some tasks may not be automated soon due to their complexity, gradually reducing the human element is seen to be the best approach to achieving full automation. In the short term, the path will likely be assistive technologies, which enhance manual operators' capabilities and extend their ability to work for longer periods.

Collaborative robots, or cobots, are assistive robots designed to work in the same vicinity as humans to assist them. The technology can improve the work environment and attractiveness of jobs while removing strenuous aspects and benefiting from the advantages offered by machinery. One challenge of implementing such technology is having a way for the robot to distinguish between human body parts and work objects while cutting. An approach proposed by Romanov et al. involves using existing relatively cheap and proven technologies such as manipulation arms, 3D cameras, augmented reality interfaces, and a robust algorithm to tie the system together (Romanov et al., 2022). The solution relies on the human operator's knowledge of the most efficient way to cut and involves a two-way communication interface between the manipulator arm and the operator. Two scenarios for the approach were suggested:

- The human operator uses the knife while the robot holds the meat and suggests the optimal cutting trajectory.
- The human operator suggests the cutting trajectory while the robot performs the cut.

The technology leverages the intricate perception of humans to evaluate the status of the cutting process, which is currently difficult to replicate through sensing technologies, while safeguarding human operators from physical harm associated with performing the tasks. This was demonstrated through experimental work conducted by Maithani et al. that used a cobot to perform a pork cut and found that the force required for cutting was reduced by 30% compared to manual operation (Maithani et al., 2021). The technology also has the potential to save the industry money by reducing the skill and physical demands of the workforce, as robots can assist in the cutting process by either performing the cuts themselves or providing suggested cutting trajectories for the operators. Currently, cobots are used for packaging, labelling, and quality control in meat processing plants, but as technology evolves, cobots will become more integrated into the meat processing industry, improving efficiency, productivity, and safety for workers.

Exoskeletons are wearable robotic technologies that are designed to enhance the physical performance of human operators. The technology is made up of a frame fitted with motors and sensors that provide support for the wearer's movements. The use of exoskeletons can be highly beneficial in industries that require repetitive physical labour and heavy lifting, such as the red meat processing industry. Exoskeletons improve workplace safety standards by reducing physical strain on workers, providing support and assistance to joints, and reducing pressure on them (Christensen & UCSD, 2023). They also stabilise the wearer's movements when using sharp tools or lifting heavy equipment or products, thereby enhancing safety in the work environment. As a result, there are fewer accidents and health issues, leading to increased productivity. The limitations of this technology for the research domain are its weight and bulkiness, and it must be carefully designed to avoid restricting the operator's motion during use (Paxman, D, Wu, & Dissanayake, 2006).

Augmented reality (AR) and virtual reality (VR) are two types of visual technologies that can be used independently or as an interface to control cobots. AR involves superimposing digital elements onto the real world to enhance the human perception of their surroundings or provide additional data. This technology is typically accessed through smartphones, goggles, or digital projections onto physical environments. AR devices are often connected to sensors or cameras that provide the presented information. Recently, AR has shown a great deal of potential in the abattoir. A case study conducted by Christensen & Engell-Nørregård showcased the technology's potential in assisting with the trimming and cutting of pork belly (Christensen & Engell-Nørregård, 2016). The study involved producing three different pork belly products from three different raw materials, which varied in weight and tissue content. The raw materials were scanned using a CT scanner and transformed into coloured maps that divided the tissues based on their densities (fat, meat, bone), with the fat thickness being represented by different colours. Operators were provided with a colour-coded fat cover, notifications of recipe ID and corrective actions, and identification of cutting lines. Despite the challenges encountered during the study, the final product showed a greater yield compared to manual operations. This technology offers operators a window to see inside the carcass, which helps them avoid mistakes that could lead to significant financial losses in the industry.

On the other hand, VR is an emersed digital simulation where the user dives into a tailored virtual world via a headset. It serves as a cutting-edge tool for testing machinery and performing tasks without worrying about the consequences. This technology has been adopted for employee training in the red meat processing industry. Providing a virtual environment of hazardous abattoirs allows employees to practice safety protocols and real-time reactions to any danger without putting themselves in harm's way. Additionally, it offers the advantage of allowing employees to practice complex cuts independently without requiring supervision or wasting resources on training.

6. Conclusion

The meat processing industry sector is a significant contributor to the Australian economy. Currently, products of this industry have an established lead on quality over overseas competitors, although the higher Australian labour costs hinder competitiveness. The arduous work environment in the deboning room and the physically and mentally demanding nature of the tasks promote automation to be seen as a key solution. However, the highly variable nature of red meat and the accurateness to which product acceptance is defined, coupled with the magnitude of deformation encountered during processes, sets an overwhelming challenge for current techniques in automation technology.

Manual operators in the deboning room use their visual and haptic senses combined with the complex ability of a human to anticipate and react to changes in real-time to perform a cut. Similarly, a robotic system capable of producing a successful product can be envisaged to perceive and interpret data correctly from the workpiece, apply corrective strategies if needed and execute cutting actions in real-time. In reviewing the attempts to develop and implement robotic systems in red meat processing, it is evident that the known successful attempts are to perform simple straight-line fixed cuts that do not require adaptability. These methods rely on preoperative scans from technologies such as X-rays, optical probes, ultrasonic sensors, vision cameras, or a combination thereof. On the other hand, tactile sensing has not been able to achieve commercial success yet. Upon reviewing these sensing technologies for real time perception over the cutting process, it was clear that all have many challenges to overcome. However, optical probes and tactile technologies are suggested for further experimental research in this area.

Although the advantages of automation for the red meat industry are well established, it is essential to recognise that developing a dependable, fully automated robotic system for implementation will take some time. The optimal approach to achieving automation in the industry is by gradually incorporating intelligence into abattoirs and reducing the reliance on manual operators. This can be achieved through the use of assistive technologies such as cobots, exoskeletons, AR, and VR. These technologies mitigate some of the limitations of human operators while still depending mainly on the presence of human operators to carry out the cutting tasks.

Credit authorship contribution statement

Basem Ade Aly: Conceptualization, Investigation, writing- original draft.

Professor Peter Brett: Conceptualization.

Dr. Tobias Low: Writing-review & editing.

Dr. Derek Long: Writing-review & editing.

Professor Craig Baillie: Writing-review & editing.

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The University of Southern Queensland is involved in the research through the supervisory team to guide the author and ensure they meet the university requirements to complete their Ph.D. by publications.

Declaration of competing interest

None.

Data availability

No data was used for the research described in the article.

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2.1.3. Links and implications

The paper "Robotics and Sensing Technologies in Red Meat Processing: A Review" discusses the complexities of implementing robotics in red meat processing, mainly due to the variability in meat properties. It explores the limitations of current robotic systems and perception methods in executing the intricate red meat cuts to the required market specifications. The paper highlights the potential of tactile sensing, a less researched technology in the red meat processing domain, drawing parallels to its successful use in medical surgeries. Tactile sensing could enable cutting robots to perceive and interpret data accurately, adjust strategies as needed, and perform cutting actions in real-time. The next chapter is a continuation of the literature review, expanding on reviewing and analysing tactile perception sensing technologies in different fields and applications.

2.2. TACTILE PERCEPTION

This chapter builds on the literature review, concentrating on the application of tactile perception in robotic red meat cutting. It also explores innovative and successful applications of tactile perception in guiding robotic systems to process similar mediums.

Red meat cutting is a sophisticated task that relies on the physical interaction between the cutting tool and the carcass. Skilled operators utilise their knowledge of meat tissue properties, strategically following or cutting along 'natural seams'—the natural divisions within the meat such as muscle groups or fat lines—to achieve precise outcomes. Operators leverage their sense of feeling, or tactile perception, to instantaneously respond to the unpredictable and deformable behaviour of red meat tissues, and to distinguish between the different tissues and interfaces.

The conventional method of applying tactile perception in robotics typically involves relying on the accuracy of numerical data provided by sensors, combined with detailed simulations of the intended task. This approach is viable for solid materials, whose properties change only under extreme conditions such as high pressure or temperature. Consequently, robots can depend on robust criteria, including precise measurements and material models for accurate predictions of process-related risks and outcomes. However, the challenge in robotic red meat cutting lies in the material's deformation and variability, which defy the assumptions made for rigid materials.

2.2.1. Mechanical features of red meat

Red meat consists mainly of viscoelastic tissues such as muscle and fat, which exhibit non-linear mechanical properties and variability both within and between specimens (Choi et al., 2013; Merenkova et al., 2020). The stiffness of these tissues is influenced by the animal’s environment, breed, and diet (MLA & AMPC, 2008; Schumacher et al., 2022).

Fat tissue is categorised into intramuscular, intermuscular, subcutaneous, and visceral fats, each characterised by unique physical properties that stem from their locations in the carcass and the compositions of their fatty acids (Lonergan et al., 2019; Sheridan et al., 1994). Muscle tissue, the primary edible part of the carcass, is structured in complex layers of connective tissues—endomysium, perimysium, and epimysium—and contains intramuscular fat, or marbling (Megías et al., 2019).

Bones also affect the behaviour of the target cut; most cuts that include bones require following the profile of the bone by cutting the connective tissues (tendons) with the muscles or cutting the ligaments between the bones (Megías et al., 2019). This composite nature of red meat results in non-uniform rheological properties during handling and processing (Nabil et al., 2015).

2.2.2. Tactile perception in dynamic environments:

Red meat cutting, culinary settings, and surgical theatres, despite their diverse applications, face similar challenges when it comes to precision cutting. These environments require real-time adaptation to handle the variable and unpredictable nature of the materials involved, such as different types of food and biological tissues. Traditional robotic cutting systems, however, often rely on pre-defined settings based on initial scans of the input product. This approach can lead to inefficiencies in cutting, increased wear on cutting implements, and potential damage to the materials being processed. Such limitations highlight the need for more adaptable and responsive robotic technologies that can better mimic the nuanced human touch.

The following sections will discuss and evaluate the role of tactile perception in enhancing systems designed for slicing red meat (beef and lamb), as well as other materials with similar properties, such as pork, various foods, and in medical surgeries.

2.2.2.1 Tactile perception in meat cutting:

Efforts have been made to utilise tactile perception for guiding cutting tools in meat processing. Scott Technology developed a system aimed at guiding a cutting tool around the intricate bone joints between the leg and the aitch bone for hindquarter cutting. However, this system did not achieve commercial success due to suboptimal yields in the final product (Steven Maunsell & Scott Technology Ltd, 2018; Ruberg, 2021). Figure 6 illustrates the complex structure of the aitch bone and compares a robot-cut piece with yield loss to the desired outcome. In a further initiative, Meat and Livestock Australia (MLA) collaborated with Mayekawa Global to refine and advance this technology, though a viable system has yet to be introduced to the market (Steven Maunsell & Scott Technology Ltd, 2018).

Figure 6: The figure shows the complex bone profile of the aitch bone and the yield loss from using robotics in deboning lamb hindquarter (Steven Maunsell & Scott Technology Ltd, 2018)

In the SRDViand (Robotis’es de D’ecoupe de Viande) research project, an attempt was made to program a robot to perform cuts for ham deboning using force control, adapting to changes and path non-uniformity in real-time (Guire et al., 2010; Subrin et al., 2011). The study focused on optimising the robotic cutting process to closely follow bone profile without causing damage or leaving excess meat. It highlighted crucial cutting parameters like angle (α), feed rate speed (Vf), and the perpendicular speed to Vf (Vn), which significantly influence cutting quality (Figure 7). For example, maintaining a cutting angle α under 30° could reduce cutting forces by 30%, minimising bone and meat damage. Force control was essential for real-time path adjustments due to variations in bone size and shape, and meat texture and firmness. This control allowed the robotic system to adjust blade pressure based on the meat's resistance, emulating a skilled butcher's touch. However, similar to previous efforts with lamb hindquarter deboning, the outcomes did not meet market specifications for the final product.

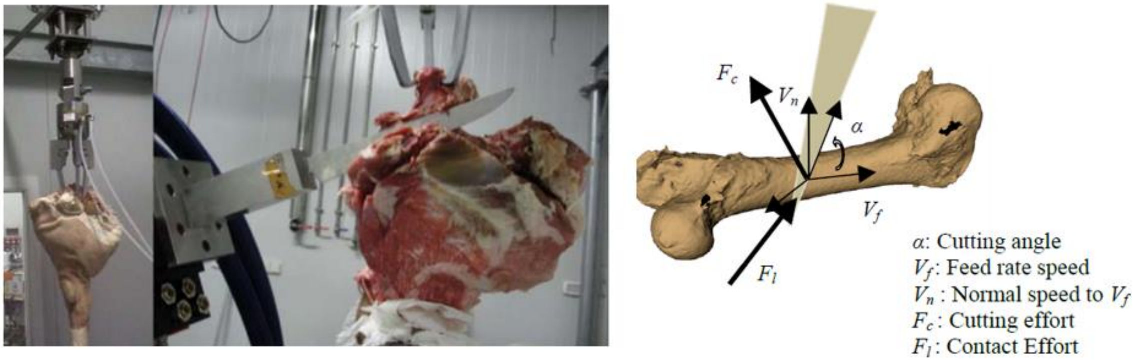


Figure 7: Robotic system for pork leg deboning and the bone cutting parameters (Guire et al., 2010; Subrin et al., 2011)

Within the same project, a strategy was proposed that combined vision and force feedback to perform a 'Z-shape cut' for beef carcass quartering (Guire et al., 2010). This approach involved separating the hindquarter from the forequarter, using the rib cage as a reference to guide the cutting tool, with real-time tactile feedback updating the tool's trajectory. In Figure 8, the cutting process begins by using visual data to position the knife at the starting point A, then follows the 13th rib with constant force from A to B. It then uses a counting system to cut through the rib cage from B to C, and concludes by moving the blade from C to D also using force sensing until a specific force level is reached, indicating the blade has cut through the spinal column. The force sensor ensures the tool maintains contact with the ribs while following their contour.

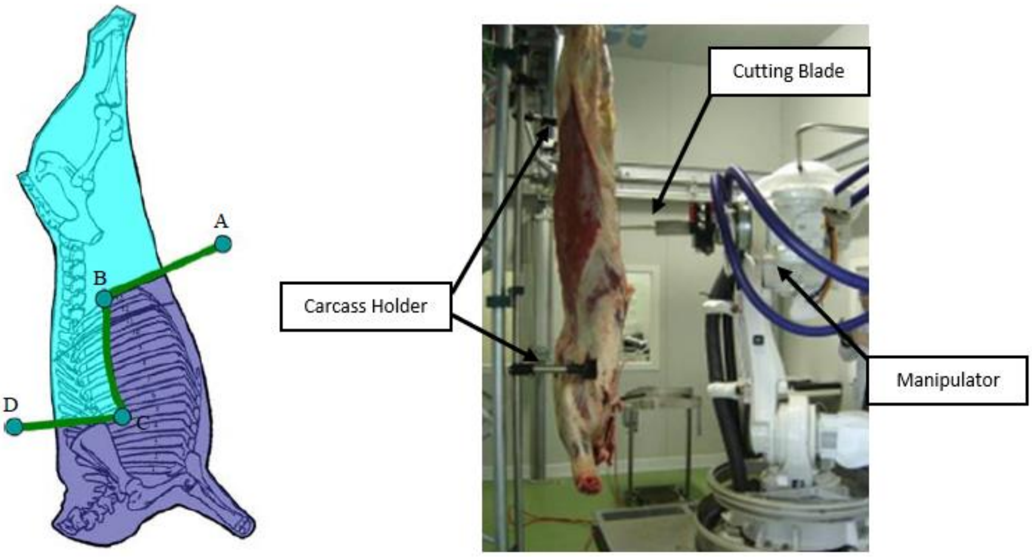


Figure 8: The cutting path of the Z-cut for beef quartering (Guire et al., 2010)

Research under project ARMS explored advanced techniques, combined material modelling and hybrid tactile/vision perception systems to automate muscle separation in meat cutting. The models' task is to anticipate the changes in the cutting medium, while the active perception technique provides a real-time update of the process' current state. Although accurately modelling the viscoelastic properties of meat in real-time is highly challenging, simpler models were suggested as a way to indicate potential behaviour rather than to predict it precisely (Cotin et al., 2000). Nabil et al. (2015) evaluated various approaches to simulate the approximate behaviour of red meat (Nabil et al., 2015). Updated versions of the mass-spring model (MSM) and tensor mass model (TMM) proved effective in representing realistic tissue motion and interactions with cutting tools while optimising computational efficiency (Han et al., 2020; Nabil et al., 2015). These models facilitated simulations of muscle separation between the round and shank, employing different approaches for cutting (*Figure 9* (a)).

Additionally, a visual-based algorithm was developed to trace the aponeurosis's trajectory by analysing the path's curvature features. An experimental setup was developed to test these strategies, featuring a robot that pulls on one side of the meat to widen the cutting path, a technique derived from manual deboning that reduces cutting force by stretching connective tissues (Figure 9 (b)) (Long et al., 2014b). Despite advancements, the robots still faced unexpected resistive forces, which impeded complete cuts. Integrating a force controller has helped detect and mitigate these forces, although this system has only been validated on foam, with further meat-cutting trials planned (Long et al., 2014a).

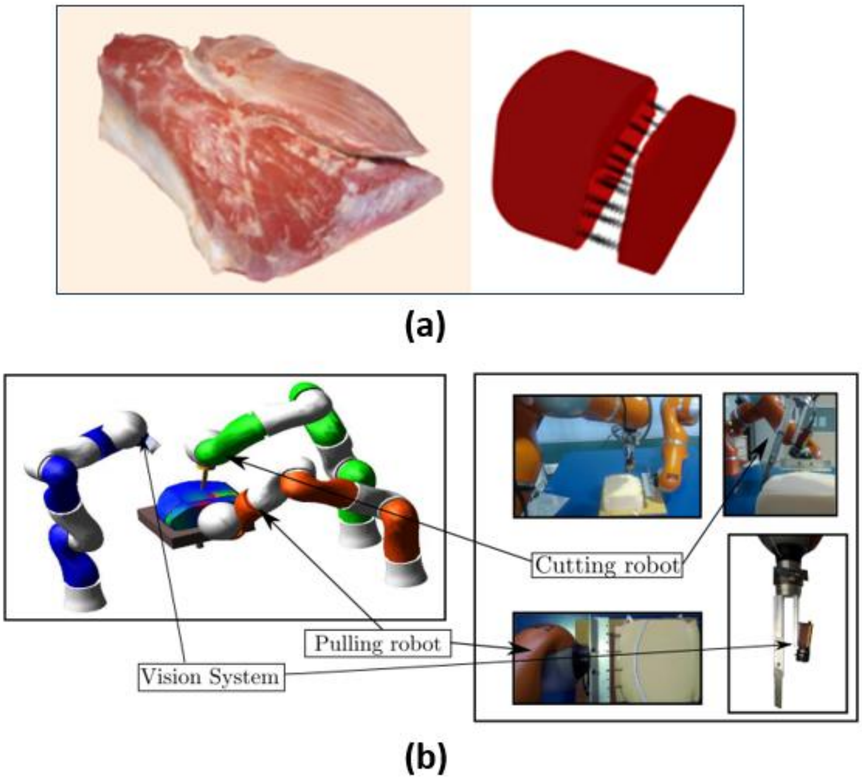


Figure 9:a) Beef round simulation (Nabil et al., 2015), b)Experimental rig for beef round muscles separation (Long et al., 2014a)

Similarly, Xie et al. developed a system that incorporated vision as a primary perception technique assisted by tactile perception for lamb hindquarter deboning. The system employed a Multi-scale Dual Attention U-Net (MDAU-Net) for the image-based segmentation of sheep carcasses, enhancing semantic segmentation accuracy critical for precise robotic cutting (Xie et al., 2021). This system also incorporates a hybrid control strategy that utilises both force and position feedback to prevent collisions with the hip bone during the cutting process. Figure 10 illustrates the cutting path generated from visual segmentation, which is to be followed with the aid of tactile perception.

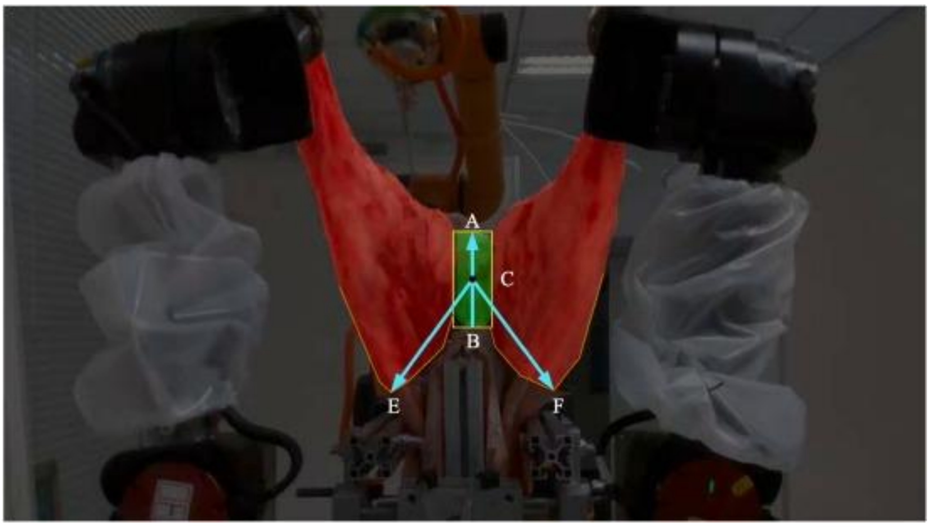


Figure 10: Cutting path around the hip bone using visual segmentation

Liu et al. (2024) developed a method that advances robotic tactile perception and control for soft tissue cutting tasks (Liu et al., 2024). Their approach utilises Dynamic Movement Primitives (DMPs) as a high-level behaviour generator to create flexible motion trajectories that mimic human operators. This is assessed by Inverse Velocity Admittance Control (IVAC), a low-level control scheme that accurately translates desired cutting paths into actual robot joint movements. Force sensor is embedded in the cutting tool, providing real-time force feedback for admittance control and tactile perception. The system's data acquisition involves capturing cutting movements and force data from multiple demonstrations, which are then encoded into a low-dimensional latent space using Principal Component Analysis (PCA) and Gaussian Mixture Models (GMM) for effective pattern recognition and behaviour prediction. Gaussian Mixture Regression (GMR) is employed to learn from this data, generating target behaviour trajectories for the robot. During operations, the robot dynamically adjusts its actions based on this learned model and real-time force feedback, ensuring precision and adaptability to variations in tissue structure. This method significantly enhances the robot's ability to perform complex cutting tasks with human-like finesse. Figure 11 displays various scenarios from the experimental work on hindquarter deboning, with the trajectories indicated.

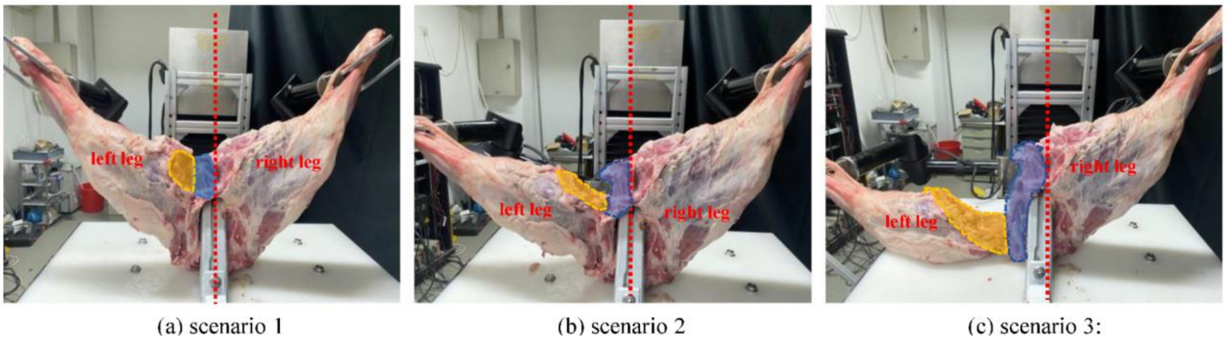


Figure 11: Different cutting scenarios generated for hindquarter deboning using machine learning (Liu et al., 2024)

Maithani et al. proposed a pHRI (Physical Human-Robot Interaction)-based assistive strategy for an industrial meat cutting system (Maithani et al., 2021). This system combines the complex perception and judgment of a human operator with real-time force feedback and advanced machine learning, utilising RNN-LSTM networks to dynamically adjust assistive forces during meat cutting operations. Impedance control, paired with force and torque sensors, ensures optimal alignment and effectiveness of the cutting tool, despite the variable nature of meat. This approach enhances both performance and ergonomic safety by leveraging tactile data for real-time control and by anticipating future actions. Figure 12 displays the system and the outcome of the approach applied to cutting foam, including a graph that plots the cutting forces exerted by a user with and without the intent prediction module. When the module is activated, the user applies only 20 percent of the force compared to when it is deactivated.

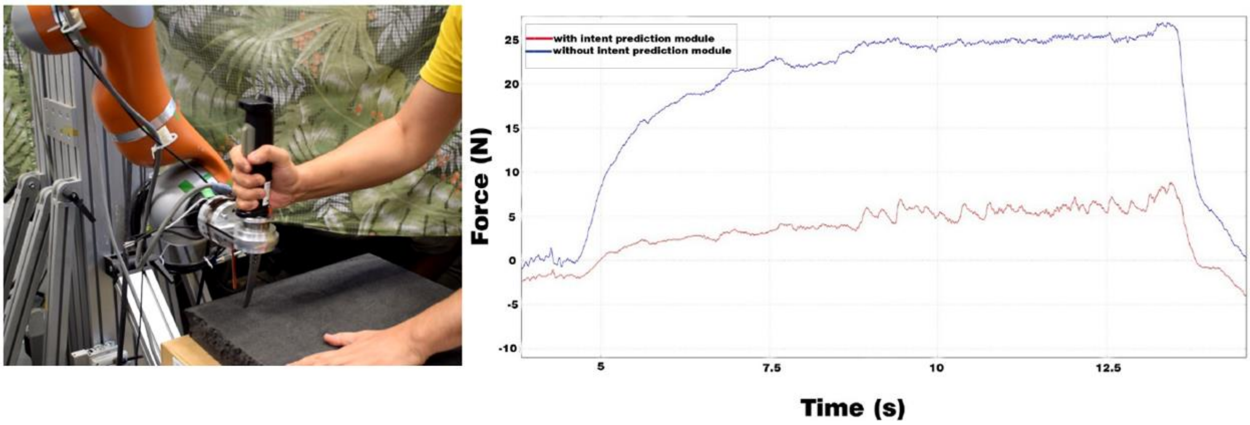


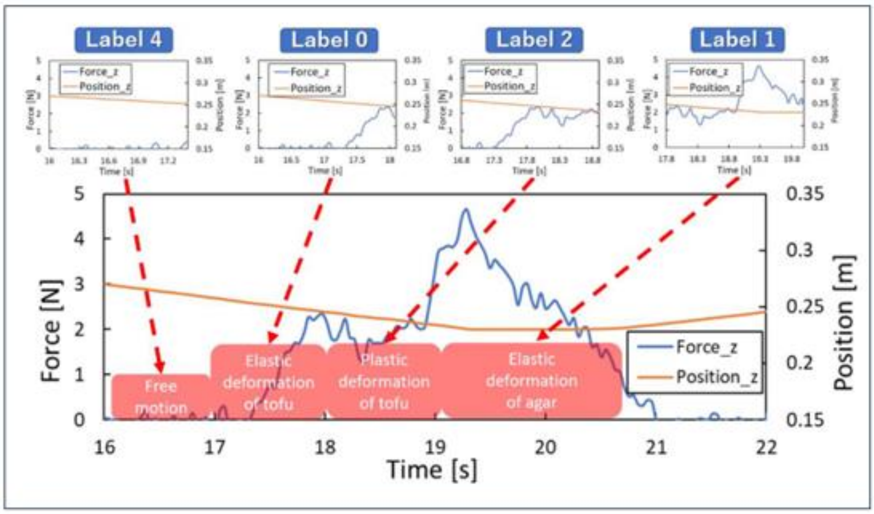
Figure 12: The cutting system and the results comparison between the forces required for cutting when the prediction module is on and off (Maithani et al., 2021)

2.2.2.2. Tactile perception in other applications:

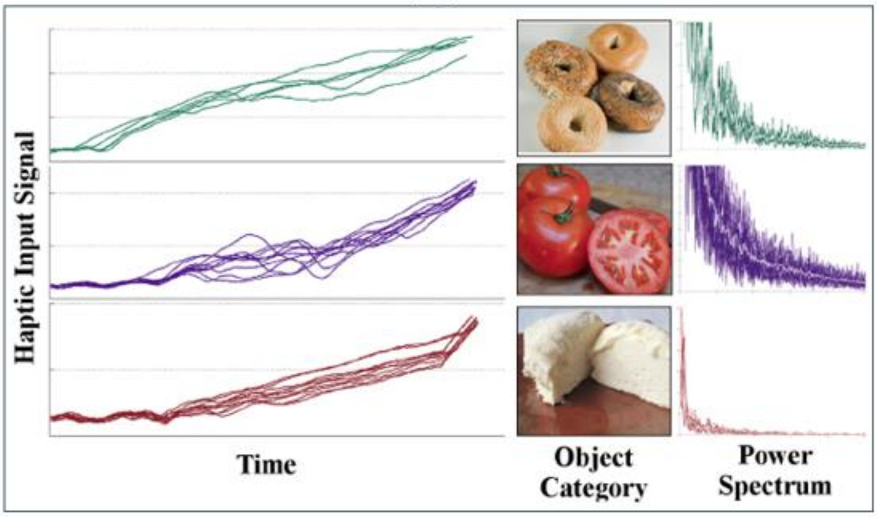
In natural environments, relying solely on raw sensor values is unreliable. Instead, it is more effective to identify persistent trends in the form of transient sensory data and use these unique patterns to discriminate between conditions and materials. This approach has been successfully applied in both culinary environments and surgical theatres, which share similar challenges in handling cutting tasks involving materials like red meat.

A study conducted by Kato et al. highlights this point through their exploration of flexible materials such as tofu and agar, analysing how these substances deform under pressure—either elastically or plastically (Kato et al., 2021). They utilised a Time-Delay Neural Network (TDNN) model, which was specifically trained to extract relevant features from force and position data collected by a robotic arm equipped with a force sensor. An example of how data transients were labelled to discriminate between the materials and their deformation states is illustrated in Figure 13 (a). The TDNN proved adept at recognising and classifying the materials based on their distinct deformation characteristics, effectively using the relationship between force changes and position as a discriminator for the type of deformation and material. The conditions investigated included both elastic and plastic deformations of tofu and agar, as well as the robot's free unstressed movements.

Similarly, a study by Gemici and Saxena explored the use of haptic data to map physical properties like hardness and adhesiveness in various food items, employing both supervised learning and Dirichlet Processes for compact representation of these properties (Figure 13 (b)) (Gemici & Saxena, 2014). This haptic-based method informed robotic manipulation strategies, enabling precise and context-aware actions necessary for complex meal preparation.



(a)



(b)

Figure 13: a)Training the TDNN model by correlating the contact state of the different materials (Kato et al., 2021), b) Features extraction of different food groups for machine learning models (Gemici & Saxena, 2014)

Spagnoli et al. demonstrated the impact of blade inclination and friction on resistance during cutting (Spagnoli et al., 2019). Their research provides theoretical and practical insights relevant to applications from industrial food processing to surgical procedures. Precise control over cutting forces, facilitated by strategies such as altering the blade's contact area or orientation, can prevent damage to delicate materials. The investigation presented the principle of oblique cutting as an example, where angling the blade reduces resistance through a slice-push effect, a technique where the blade is angled to effectively combine slicing and pushing motions.

Xiaoqian Mu and Yan-Bin Jia used a similar approach to develop a method that enhances robotic cutting systems by enabling robots to adapt by optimising knife trajectories based on real-time estimations of material properties (Mu & Jia, 2022). Using a recursive least-squares algorithm, their system estimates critical material properties, such as Poisson's ratio, fracture toughness, and the coefficient of friction from data collected via force and torque sensors attached to the knife. With these parameters, the system can dynamically generate knife trajectories that optimise cutting effectiveness. By setting an appropriate slice-push ratio the system can significantly reduce the force required for cutting while improving the precision and smoothness of the cuts. However, the current optimization method primarily uses local, immediate sensor data to adjust trajectories, which may not provide the best path for complex tasks. The authors suggest potential improvements, such as employing advanced algorithms like Model Predictive Control, which would take future conditions into account, and expanding the method to include knife rotations for a more comprehensive cutting strategy.

The medical field has utilised force and torque sensors to develop real-time informative sensing techniques with micro-level accuracy. The technology is very effective in minimally invasive surgeries (MIS); given the surgeon's perception and dexterity limitation, the operation becomes significantly challenging (Bandari et al., 2019). Adding haptic technology helps improve surgery results by increasing tools' precision and stability (Moreira et al., 2014). A few minimally invasive surgeries utilise such technology to provide precise control during operations and reduce any potential tissue damage or injuries.

Needle insertion in surgeries is an application that benefits from force feedback. Force can provide valuable information regarding the depth and trajectory of the needle, discriminate between the tissues, and provide control feedback to minimise tissue deformation and needle deflection (Abolhassani, Patel, & Ayazi, 2007). Cheng et al. created a finite element simulation based on experimental results of a needle inserted in a homogenous phantom with different velocities (Cheng et al., 2015). The phantom represented the muscle tissue and was used to provide more consistent results for testing purposes. The experiment aimed to interpret the resultant forces on the needle tip. The force analysis was based on a previous study by Okamura et al. that identifies the total force acting on a needle, including cutting force to penetrate the first tissue, stiffness force from deformation, and friction force (Okamura et al., 2004). Cheng et al. improved this theoretical framework by considering the effect of tissue viscosity.

The experiment results showed the relation between the total force with needle depth and material viscosity at different velocities. A consistent force increase was presented the deeper the needle penetrates the sample, and the force required increases with the velocity. Since the needle bevel is very sharp, the force to fracture the phantom is too small, and the resultant forces are due to viscosity and friction that increase with needle velocity and depth.

The epidural procedure is another medical application that has benefited from the correct interpretation of force. It involves the insertion of Tuohy needle to apply anaesthetic in the epidural cavity. Brett et al. developed a mechanical simulator based on tactile information derived from experiments for training purposes and a handheld tool to feed the needle at a constant speed (Brett et al., 2000; Peter N Brett et al., 1997; Cotin et al., 2000). The experiments correlated the force data relative to the occurring actions and needle position in the different tissues. There are three main mediums initial membrane (skin), fatty tissue, ligament tissues (supraspinous ligament, interspinous ligament), and finally, the ligament cavity interface (ligamentum flavum) before entering the epidural cavity.

Two experimental tools were developed for tests (Brett et al., 2000). An automated needle tool equipped with a strain gauge force sensor and pressure transducer to measure feed force and pressure inside the laboratory. A needle and syringe equipped with a piezoresistive sensor to measure fluid pressure for experiments performed outside the laboratory.

The needles were inserted with different velocities. Similar results were obtained with minor differences between the two tools. Throughout all the results, similar transients and trends were observed that were averaged and summed up in Figure 14**.**

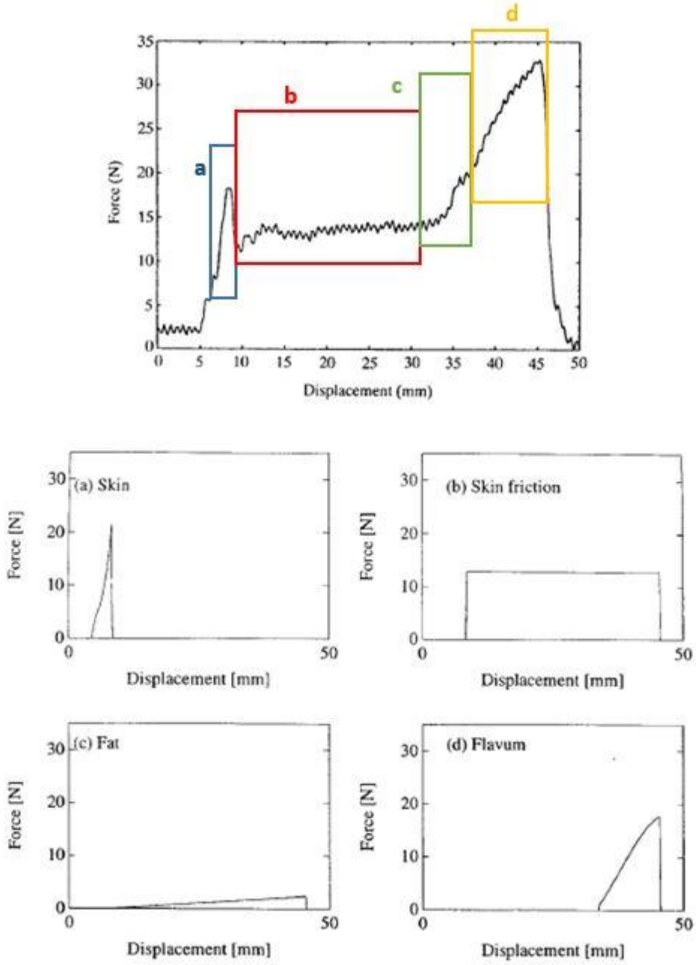


Figure 14: The unique force transients during the epidural procedure (Peter N Brett et al., 1997)

Two high peaks of accumulated resistive force define the responses of elastic and viscoelastic behaviour prior to the penetration of the skin membrane and the ligaments before the epidural cavity (regions **a** and **d**). Region **b** shows a steadier force profile due to the friction between the needle shaft and the surrounding skin tissue. Finally, in region **c,** the fatty tissue that has the behaviour of viscous fluid applying a slightly increasing resistive force proportional to the length of the needle within it.

Utilising a similar approach, Brett et al. developed one of the few successful examples of adapting tactile technology into tissue-guided surgical robotics represented in handheld cobot drills for cochleostomy surgical procedures (Brett et al., 2007). The drilling system assists the surgeons in drilling through the cochlea bone without penetrating the membrane behind it. The control system is required to accurately detect the drill bit's position relative to bone tissue interfaces and account for the compliant behaviour of the bone. The drill is guided by force and torque feedback from the drill bit. The proper interpretation of the transient signatures of force and torque provides information to anticipate conditions on the cutting path and to locate with precision the burr of the drill relative to tissue interfaces. The method divided the trajectory of the drill into four main events to discriminate and control critical stages in the process.

Figure 15 shows how the force and torque vary with tissue depth throughout the drilling process.

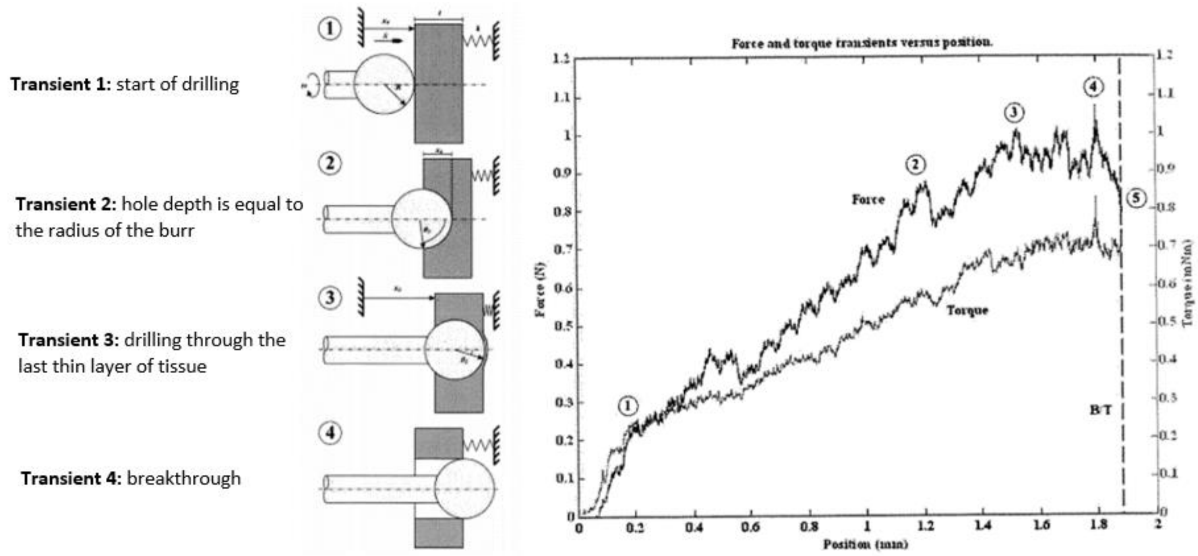


Figure 15: Force transients during the drilling process (Taylor, 2008)

2.2.3. Conclusion

The chapter highlights the potential and possibilities of tactile sensing technology in robotics, particularly in applications with similar characteristics as red meat cutting. The reviewed methods of implementing tactile sensing include using it as the primary perception method, integrating it into hybrid systems combined with vision, simulation models, or machine learning. Among these innovative techniques, the most promising ones utilise tactile perception in a manner similar to human sensory processing, focusing not on the numerical values of the tactile data but on discriminating between different mediums and conditions.

The potential of tactile-sensing technology can be identified from use in reviewed applications where there are distinct parallels in medium characteristics with red meat. The reported method for discriminating natural deformable materials and their characteristics offers possibilities for cutting red meat. Similarly, guiding a knife through red meat tissues to perform a cut requires developing a technique that can discriminate between the unique features of the cutting mediums and react to the prominent conditions in real-time through a fundamental understanding of critical process events and identify methods to detect them. The learnings from the reviewed applications emphasise the importance of the reactive transients in tactile feedback as an identification tool for the detectable materialistic features and states of red meat tissues.

A robotic system capable of producing a successful product can be envisaged to perceive and interpret data correctly from the workpiece, apply corrective strategies if needed and execute cutting actions in real-time. In reviewing the attempts to develop and implement robotic systems in red meat processing, it is evident that the known successful attempts of red meat cutting are to perform simple straight-line cuts that do not require adaptability. Other trials to follow more complex cutting profiles using tactile perception proved the need to step back and start from the basics to understand the data perceived and how it can indicate the changing structure and behaviour of red meat in simpler cuts.

The next chapter outlines the methodology used to study tactile perception in red meat cutting. It covers the experiment's structure, the various cutting variables and how they are addressed, the experimental equipment, and the cutting model. This model explains the forces exerted on the knife during cutting and how these forces are distributed.

CHAPTER 3: METHODOLOGY

This chapter details the methodology and experimental design used to investigate tactile perception in robotic red meat cutting. The systematic review in Chapter 2 highlights the shortcomings of conventional sensing techniques in guiding robotic cutting of red meat and identifies a significant gap in our understanding of the role of tactile perception in this area. It also shows the absence of thorough studies that provide detailed information and results on the challenges encountered when robots process red meat using tactile perception. This gap in research prompted the development of the experimental approach of this study, designed to advance our fundamental understanding of tactile perception in robotic red meat cutting.

3.1. Experiments structure

The primary objective of this study is to establish a novel, fundamental understanding of how tactile perception can be utilised to guide a robotic red meat cutting. The experiments conducted are aimed at answering 5 main research questions:

Question 1: What consistent mechanical features in red meat tissues can be reliably detected using tactile perception?

Question 2: How feasible and precise is tactile perception in identifying red meat tissue features and behaviour during cutting?

Question 3: What are the persistent unique transients in the tactile data that discriminate tissues and their interfaces?

Question 4: How can the unique force transients related to the mechanical features of red meat be interpreted to identify key cutting events?

Question 5: Can tactile perception-based techniques inform a control strategy to guide a cutting knife toward an automated cutting system?

The experiments were structured to progressively explore robotic meat cutting throughout the study. Initially, the variables involved in the cutting process were simplified for basic fundamental research. As the research progressed, the gained knowledge facilitated a systematic addition of complexity to the experiments. This incremental strategy was essential for managing the inherent uncertainties and challenges of robotic meat manipulation. Such a phased approach ensures that each layer of added complexity is well-informed by the insights gained in the preceding stages, thereby enhancing the robustness and relevance of the findings. The following list will present the sequence and structure of the experiments in the thesis.

3.1.1. Experiment 1: tactile sensing for tissue discrimination in robotic meat cutting: a feasibility study (Section 4.1)

Aim:

The experiment investigates the feasibility and accuracy of tactile perception in discriminating between red meat tissues and identifying specific cutting events under controlled conditions in a defined observational setup.

Procedure:

Simple straight-line cuts were performed across various tissues and interfaces to observe the tactile data response. The setup aimed to investigate cutting actions and phenomena during straight-line cuts that travel through fat tissue, muscle tissue, and their interfaces in one motion.

A total of 18 cutting tests were conducted using two striploin chop pieces, split across four sides. In half of the tests, the cutting began from the muscle side towards the fat layer, and in the remaining half, it started from the fat layer towards the muscle. The knife was positioned vertically to the test sample surface, aligned with the cutting path, and operated at a fixed feed velocity of 20 mm/sec for better control. The cut depth was approximately 20 mm, measured by moving the knife downward from the upper surface of the sample. The sample temperature was maintained at approximately 9°C to simulate abattoir conditions. Figure 16 presents the cutting trajectories, and Table 3 lists the experiment's variables.

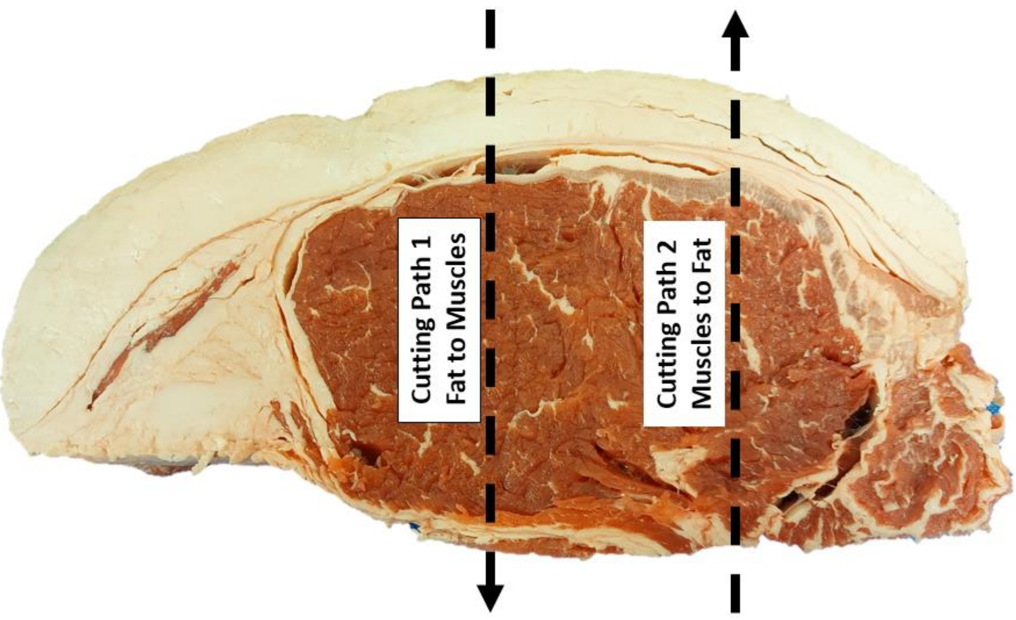


Figure 16: Cutting trajectories of experiment 1

Table 3: Experiment 1 variables

Type of cut	Striploin steaks
Total number of cuts performed	18 cuts
Cutting Tissues	Fat layer and muscles
Cutting Speed	20 mm/Sec
Sample Temperature	≈ 9°C
Cutting depth	≈ 20 mm.

Data analysis:

The force transients captured in the tactile data are processed and analysed to correlate with the location of the knife within the sample. Cross-correlation analysis of the data was undertaken to identify patterns and similarities in the force profiles across different tissues. This analysis aimed to interpret how these distinct force transients represent various cutting events and to evaluate their consistency when identical cuts were made on the same tissue arrangements. The extracted data focused on the force component in the X-axis, which corresponds to the direction of the cut affecting the tip of the knife.

3.1.2. Experiment 2: sensitivity of cutting force transients to the depth of cut (Section 1 of Chapter 4)

Aim:

The experiment explores how variations in cutting depth affect the ability to discriminate unique force transients related to tissues, their interfaces, and overall product behaviour. It follows Experiment 1 to address challenges in maintaining consistent cutting depths due to the non-uniform characteristics of the meat.

Procedure:

Following a similar approach as in Experiment 1, the robot performed linear cuts on striploin chops at three different depths: 10 mm, 20 mm, and 30 mm. The depths were measured from the upper surface of the test sample by moving the knife downward in the Z direction (Figure 17). Each depth was tested twice, totalling six trials. The cuts were made across fat tissue, muscle tissue, and their interfaces. The cutting velocity was fixed at 20 mm/sec, and the sample temperature was approximately 9°C during the experiments. This method allowed for a systematic exploration of how varying cutting depths affect the cutting force and tissue interaction, considering the inherent properties of meat tissues such as stiffness and deformation.

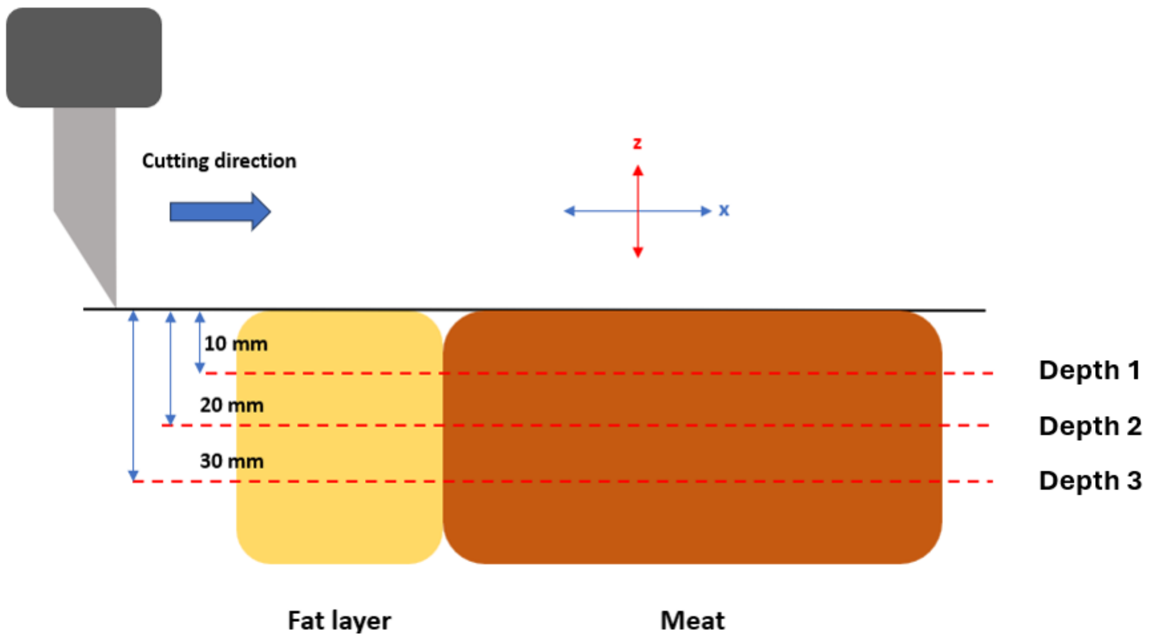


Figure 17: Experiment 2 cutting paths at different depths measured from the upper surface of the test samples

Table 4: Experiment 2 variables

Type of cut	Striploin steaks
Total number of cuts performed	6 cuts
Cutting Tissues	Fat layer and muscles
Cutting Speed	20 mm/Sec
Sample Temperature	≈ 9°C
Cutting depth	≈ 10, 20 & 30 mm.

<u>Data analysis:</u>

The analysis concentrated on comparing the force transients for similar tissue arrangements at different depths. Cross-correlation analysis and visual observations were used to assess the impact of depth on the force data and identify the unique force transients related to different tissue features.

3.1.3. Experiment 3: robotic fat trimming: characterisation of red meat tissue structure using tactile perception (Sections 5.1 & 5.2)

<u>Aim:</u>

This experiment adds the lateral force on the side of the knife as another source of tactile data that, combined with the forces on the tip of the knife, gives more details about the tissue structure and behaviour around the knife. The study aims to use tactile sensory data transients along two orthogonal axes on the knife to characterize the force transients of a robotic knife while trimming fat from striploin steaks relative to the fat/lean interface, focusing on how these forces vary at critical cutting events while trimming, such as leaving the fat layer or approaching tissue interfaces, and the ability to guide the knife based on these variations.

<u>Procedure:</u>

The study conducted a total of 17 straight-line cuts over the sides of six different pieces of striploin steaks test samples in the fat layer with different angles and distances relative to the fat/lean interface to mimic different cutting movements in the trimming of striploin steaks. Figure 18 shows a representation of the cutting paths in the experiment. Out of those cuts, 8 were directed away from the fat/lean interface towards the outer edge of the fat layer, and 9 interacted with the fat/lean interface and the surrounding natural path between the fat layer. The cutting velocity was fixed at 20 mm/sec, and the sample temperature was approximately 9°C during the experiments.

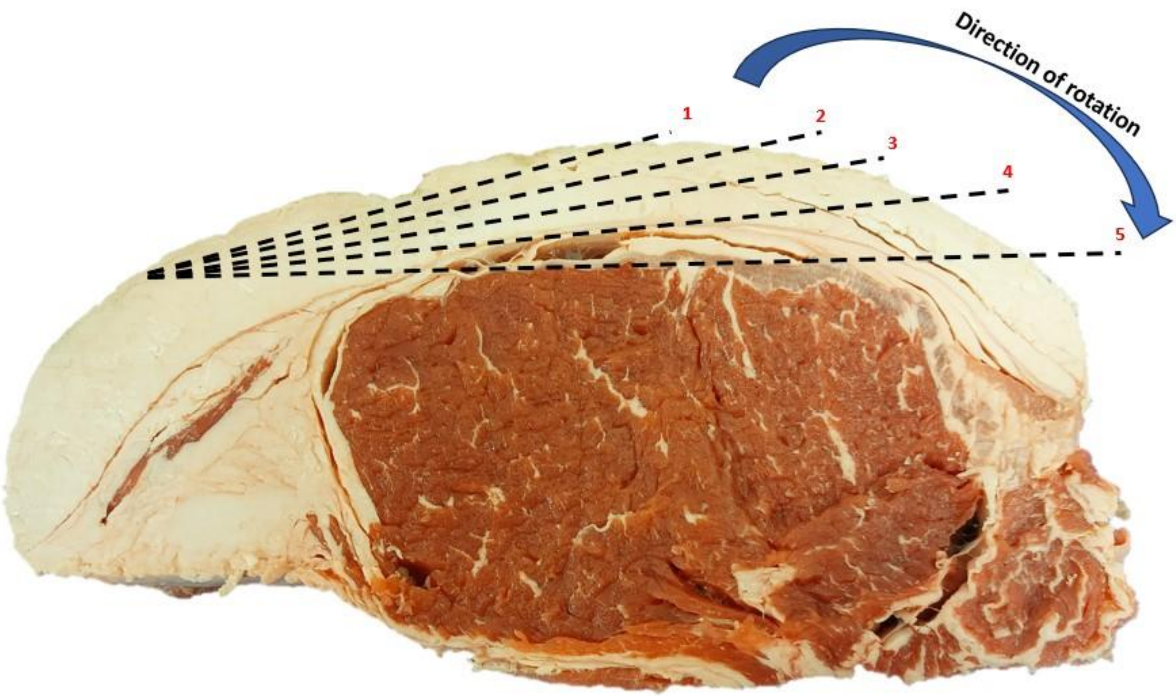


Figure 18: A representation of the cutting trajectories in experiment 3

Table 5: Experiment 3 variables

Type of cut	Striploin steaks
Total number of cuts performed	17 cuts
Cutting Tissues	Fat layer with different angles and distances from the fat/lean interface
Cutting Speed	20 mm/Sec
Sample Temperature	≈ 9°C
Cutting depth	≈ 20 mm.

Data analysis:

The analysis focused on the interpretation of the unique force transients of F_x (forces on the tip of the knife) and F_y (lateral forces) within the context of the occurring cutting event. The analysis included visual observations of the trends in the data patterns, applying different types of correlation analysis between the forces and observing the rate of change of the lateral force as a way to inform the effective direction of the forces on the sides of the knife.

3.2. Addressing key variables related to robotic meat cutting

The primary challenges of integrating robotics into the red meat industry, as explained in Chapter 2, revolve around the variability in carcass structure and the unpredictable behaviour of red meat tissues. This unpredictability is observed both in stationary states, affected by factors such as temperature and gravity, and in response to external forces applied during handling and cutting. The distinctive characteristics and properties of red meat carcasses require specialised manipulation techniques, adapted to the shape and features of the desired cut. Additionally, a specialised cutting tool is required to access the target seams for effective cutting.

This research explores an approach leveraging tactile temporal sensory data to discriminate meat tissues and tissue interfaces in real-time. The strategy correlates unique force transients in the force data with materialistic features of the carcass and key cutting events of the task. Within the context of this scope, the variables involved in red meat cutting were addressed as follows:

Inconsistent presentation of each workpiece:

1- The dimensions of the input products are challenging to determine accurately.

2- The size of each workpiece can change drastically.
3- The structure of each workpiece is non-uniform.
4- Tissue distribution and tissue interface placement can vary between carcases, which changes the location of the cutting path.

The first three factors significantly impact the optimal manipulation technique, including how the carcass is held and interfaced with the knife, and the selection of the appropriate cutting tool to reach and follow the intended cutting trajectory. These challenges, identified in the literature review chapter, are acknowledged as research gaps in the implementation of robotics in the red meat industry and warrant further investigation. These factors were addressed and simplified in this study by selecting striploin steaks as the test samples.

The striploin steak, a simple yet high-value product, is produced by sectioning the striploin primary cut from the beef carcass. The striploin is estimated to be worth approximately 15% of the carcass value. The dimensions and weight of the striploin primary and an average of the striploin steak dimensions are presented in Figure 19 and Table 6 (Border et al., 2019; Khodabandehloo, 2018; Standard, 2015).

With its well-defined tissue interfaces, the striploin steak serves as an appropriate model for evaluating the precision and efficacy of robotic cutting techniques. Its relatively uniform thickness and predictable structure allow for controlled experimental conditions, while still capturing the typical variations found in red meat. In this study, the manipulation technique involved a simple fixation of the carcass in front of the cutting tool, which was a deboning knife. This choice was made because the non-powered deboning knife is the most commonly used tool for slicing and helps reduce some of the complexities that might arise if an electrically powered tool were used, as such tools could influence the force data. This approach ensures a consistent and representative environment for testing tactile perception in robotic meat cutting.

The fourth factor is one of this study's points of focus: exploring the capability and sensitivity of tactile perception to discriminate different tissues and their interfaces and to locate the cutting tool relative to these features.

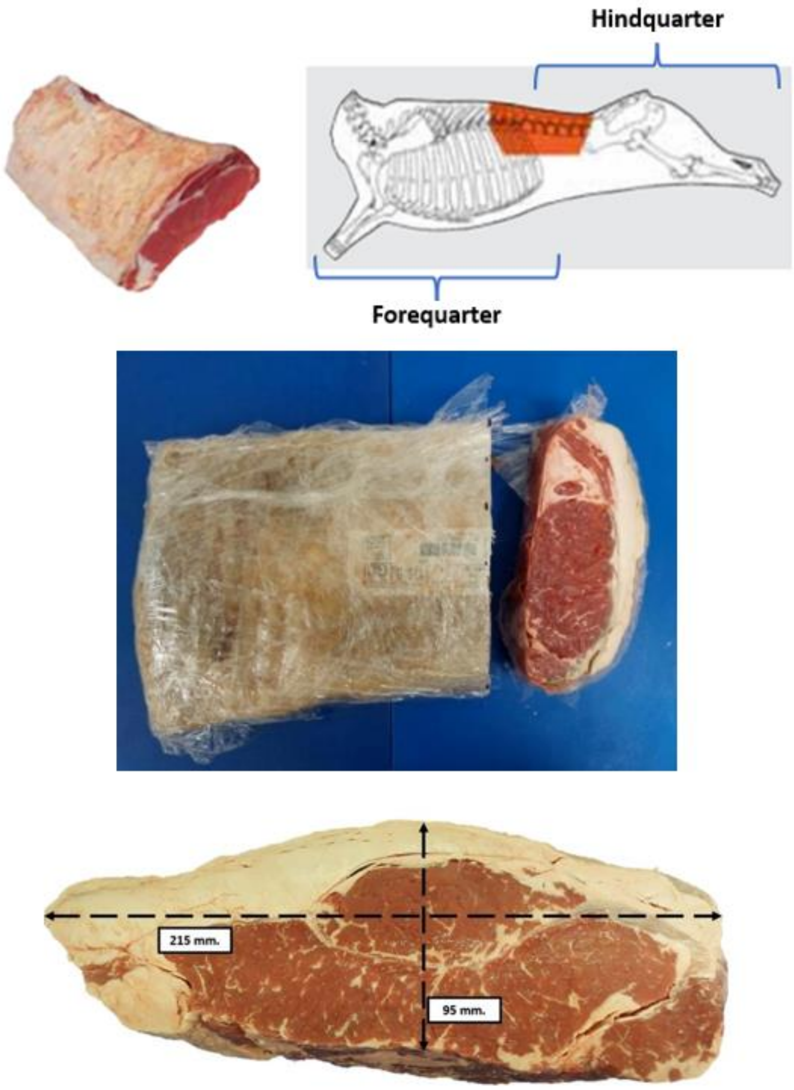


Figure 19: Primary unprocessed striploin product and measurements of a striploin chop

Table 6: Measurements of a striploin cut (Khodabandehloo, 2018)

	Maximum	*Minimum*
Length	605 mm.	450 mm.
Width	245 mm.	200 mm.
Height	125 mm.	90 mm.
Weight	13 Kg.	5.4 Kg.

Unpredictable tissue behaviour and responses

1- Meat relaxation with time due to the variation in gravitational force vectors, inertial forces, and the changes in the ambient temperature.
2- Transient deformations are induced by cutting tool forces during the cutting process affected by the speed of cutting, the sharpness of the cutting tool and the depth of the cutting tool in the tissues.

To address the first factor, the temperature of the test samples was maintained at 9°C throughout the experiment, mirroring the temperature conditions of deboning rooms in abattoirs. Test samples were stored in a sealed container in the refrigerator and were only removed immediately before experimentation. This approach helped mitigate meat relaxation, as meat becomes more malleable with temperature increases. The impact of gravitational forces is more pronounced on hanging carcasses and larger cuts. In this study, striploin steaks were placed on a flat surface at all times, including during experiments, to minimise the influence of gravitational forces.

The second factor is central to the scope of this research, focusing on observing tissue deformation at various cutting stages. Deformation serves as a direct indicator of tissue rigidity and provides a robust indication of the knife's location during different cutting phases. Influential factors such as the speed of the knife were kept constant at 20 mm/s. This speed was found to be appropriate to prevent meat clamping around the knife. The depth of the knife inside the cut is another factor that could not be controlled and is part of the research investigation.

To summarise the factors involved in the experiments, Table 7 illustrate these factors and how they are addressed in the experiments.

Table 7: Addressing the cutting variables during the experiments

Dimension and Structure	- Striploin steaks are cut into portions with similar dimensions (Figure 19 & Table 6). - Striploin steaks have a relatively consistent structure and tissue arrangement. - Striploin steaks have an almost two-dimensional tissue representation, facilitating visual observations.
Handling and Manipulation	- A simple manipulation technique was used by securing the test sample against the knife with custom-made meat clamps and holding corners.
Temperature	- Approximately 9°C to match the temperature of deboning rooms.
Speed	- A speed of 20 m/sec was chosen for better control over the cutting process and to prevent excessive deformability and meat clamping around the knife.

Depth	- As mentioned in Section 3.1.2, titled "Experiment 2: Sensitivity of Cutting Force Transients to the Depth of Cut," the depth is investigated as a variable in Chapter 4 at 10 mm, 20 mm, and 30 mm.
Cutting Tool	- A slicing knife, typically used in meat slicing tasks, is recommended by skilled butchers.
Sharpness	- Three knives were used across the experiments; a different knife was used for each experiment to ensure sharpness. Each knife performed approximately 11 cuts.
Cutting Angle Relative to the Sample Surface	- The knife is perpendicular to the meat's surface plane.
Cutting Trajectories	- Straight line cuts relative to the sample features.
Mediums of Cuts	- Muscles and fat tissues.

3.3. Equipment

The testing equipment setup used in the experiments was designed for flexibility, accommodating the needs of this research and adaptable for future studies within the same field. Consequently, not all equipment is fully utilised at this stage. The components used in the experiments include (Figure 20):

- ABB IRB 1200 manipulator with 6-axis movement capability.
- ABB 6-axis force sensor 165.
- Static deboning knife (see Appendix D for more details about its features and specifications).
- Clamps and holding corners to secure the meat.
- Sony FDR-X3000 action cameras.

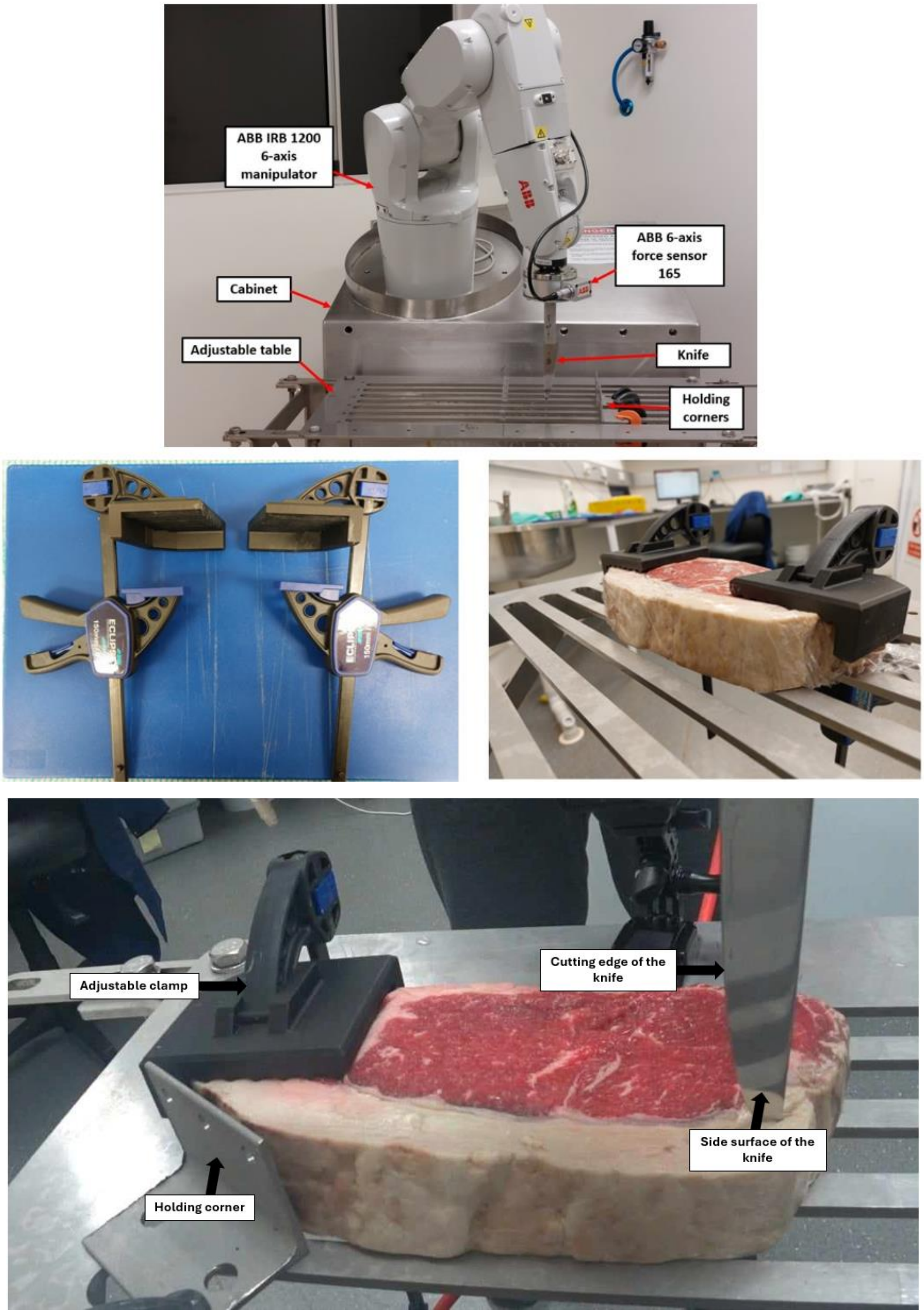


Figure 20: Test rig setup

3.4. Experimental Procedure

3.4.1. Preparatory steps

Before starting the experiments, essential preparatory steps were undertaken. These included load identification and calibration of the force sensor. Load identification was performed using an internal recorded program on the robot. The task of this program is to identify the components mounted on the robot, which include the force sensor, knife bracket, and knife. The identification process calculated and recorded critical parameters such as weight, dimensions, inertia, and the tool centre point of the attached knife. Based on the tool centre point, the operational space of the knife, including its coordinates, was established. The robot's work object was adjusted to align the knife's movement orientation with the axes of the force sensor. This alignment ensures that the cutting direction movement corresponds to the F_x axis of the force sensor, while the perpendicular direction aligns with the F_y axis, which measures the side forces on the knife. The force sensor was calibrated to detect contact forces while filtering out the effects of gravitational forces. See Appendix C for further details on the force calibration process.

3.4.2. Cutting process setup

The robot was programmed to guide the knife along a predetermined path perpendicular to the plane of the test sample. An internal timer was activated at the start of the cutting process. After each experiment, the robot recorded the knife's coordinates, the timer readings from when the knife began to move, and the corresponding force measurements, saving these as a .csv file.

3.4.3. Video documentation

The experimental procedure was documented using two Sony FDR-X3000 action cameras placed to capture the knife's position and the test sample's behaviour during cutting.

3.4.4. Video and data synchronisation

To correlate the knife's position with force readings accurately, the timers of the recorded videos were synchronised with the robot's internal timer. Videos of the cutting process were edited to start precisely when the knife began to move, aligning with the start of the robot's internal timer. This synchronization allowed timestamps in the videos to be reliably correlated with the force data captured by the sensor.

3.4.5. Data analysis

The combined data from the force sensor and the video footage facilitated the derivation of a force-time series during the cutting process. This data could be correlated with the properties of the tissue and its reaction during cutting, providing deeper insight into the mechanical interactions involved. After each experiment concluded, MATLAB was utilised to process the data and generate the corresponding graphs.

3.5. Modelling of cutting forces in robotic meat cutting

This section describes a concept as a model to explain the cutting force transients in the tactile sensory data taking place during specific yet crucial stages of a straight-line cutting across different tissues. The approach draws inspiration from similar models (Azar & Hayward, 2008; Hu et al., 2012; Khadem et al., 2016; Okamura et al., 2004) of force descriptions applied to explain tissue fracturing within clinical surgical applications where there are similar phenomena in cutting and penetration processes.

Force, by definition, is a vector quantity that possesses both magnitude and direction. In the context of cutting meat tissues, the total applied cutting force F_{Total} in the X direction affecting the leading edge of the knife can be described as the sum of compressive and frictional components (Khadem et al., 2016; Okamura et al., 2004). The compressive force component $F_{Compressive}$ is the reaction to the cutting of tissues (Figure 21). The frictional force $F_{Friction}$ is the reactive component to resistive forces, attributed to the interaction with the tissue acting as shear on the sides of the knife.

The compressive reactive force component $F_{Compressive}$ acting on the knife during the slicing of meat tissues can be described as the sum of two further distinct force components: the component required to initiate a crack at the surface such that the blade enters the tissues ($F_{Cutting}$) and the component reacting to elastic tissue deformation ($F_{Deformation}$). The lateral force in the Y direction (F_y) on the side surfaces of the knife is primarily due to the side pressure from tissue deformation.

Then

$$F_X = F_{Total} = F_{Compressive} + F_{Friction} \qquad (1)$$

Where

$$F_{Compressive} = F_{Cutting} + F_{Deformation} \qquad (2)$$

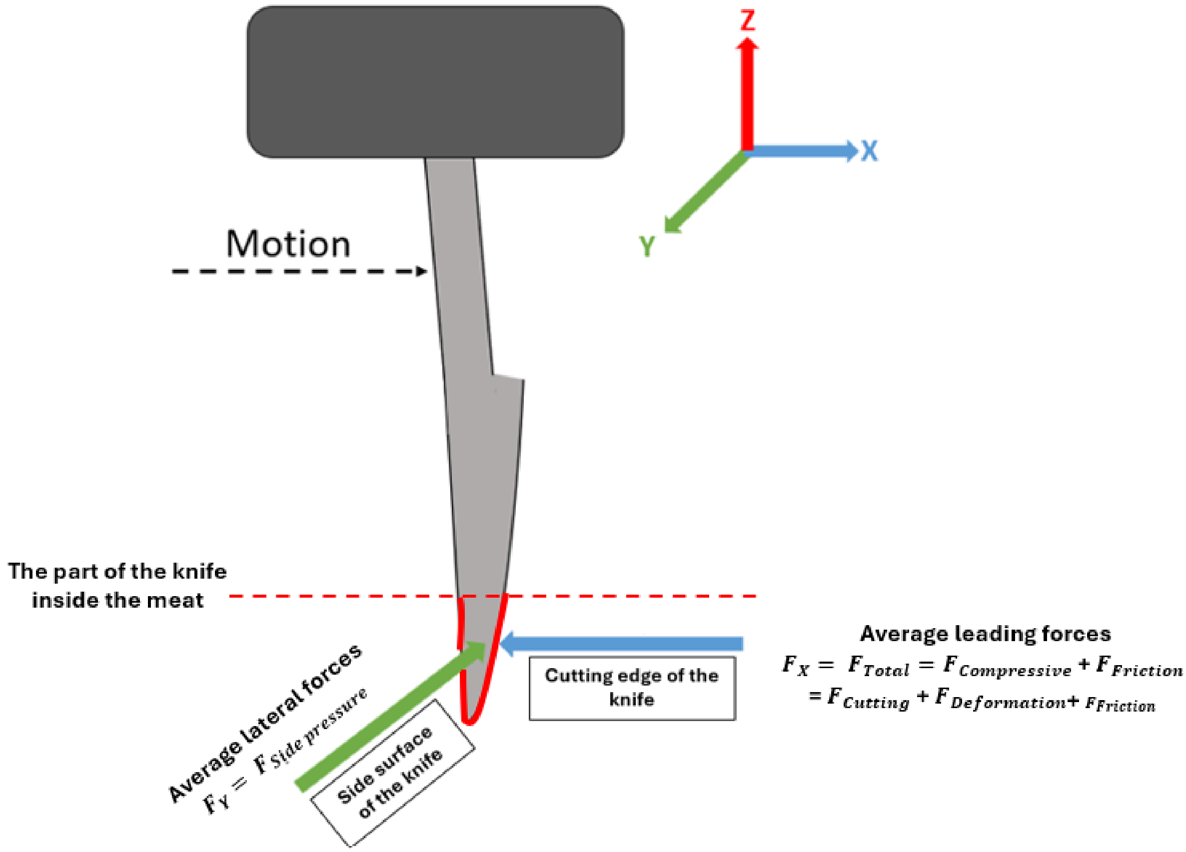


Figure 21: Free body diagram represents the force components acting on the knife blade

Since the tissues undergo elastic fracture, where they deform to a structural limit before fracturing, the deformation around the crack is non-reversible or plastic. The process is considered quasi-static, where the cutting speed is sufficiently slow and maintains equilibrium. Energy conservation can be used to explain factors affecting forces at different stages of cutting. Expressed as equation (3) (Azar & Hayward, 2008; Hu et al., 2012),

$$\boldsymbol{Fdu} + \boldsymbol{dU_i} = \boldsymbol{J_{IC}}\ \boldsymbol{dA} + \boldsymbol{d\Delta} + \boldsymbol{P}\ \boldsymbol{du} \qquad (3)$$

Where

$\boldsymbol{Fdu}$ is the work done by the knife cutting to an effective force **F** during a displacement of $\boldsymbol{du}$

$\boldsymbol{U_i}$ is the strain energy stored in the membrane before any external forces are applied. The tissues are considered at rest and $\boldsymbol{dU_i}$ is zero;

$\boldsymbol{J_{IC}}\ \boldsymbol{dA}$ is the resistance to fracture the tissues $\boldsymbol{J_{IC}}$ at a cutting surface area of $\boldsymbol{dA}$;

$\boldsymbol{d}\Delta$ is the stored elastic energy in the tissues during deformation;

$\boldsymbol{P\ du}$ is the work done by the friction force **P** to resist the knife movement during the displacement $\boldsymbol{d}$

As the knife penetrates the first layer of tissue (Figure 22), the blade causes the tissue to deform from its steady state position. With increasing force from the knife, the tissue continues to deform, reaching its structural limit when penetrated. At this stage, there is negligible friction or resistance caused by tissue fracture, and the response of the meat tissue relative to the knife position is entirely due to the release of internal elastic energy stored in the tissues during deformation. Consequently, equation (3) is adjusted accordingly:

$$\boldsymbol{Fdu} = \boldsymbol{d}\Delta \qquad (4)$$

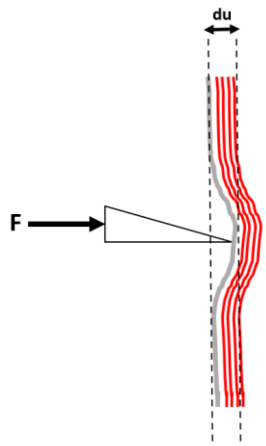


Figure 22: First tissue interface penetration

The equation shows that the applied force causes elastic deformation of the first tissue layer. It is known that for meat tissues, the force is related to displacement by a non-linear function. The effect is elastic with temporal as a result of stress relaxation. For purposes of describing the mechanisms, the linear behaviour is assumed and described by Hooke's law (Mavko et al., 2020). The value of the elastic modulus is determined by the stiffness of the tissue layer during the cutting conditions, such as temperature, which affects the value of the required deforming force. Figure 6 (a) in Chapter 4 shows the deformation difference between the muscles and fat. In this area, the force transient shows an increasing trend until the knife fully penetrates the first interface.

After the knife penetrates the surface of the first layer of tissue, the initial crack propagates in the direction of cutting and equation (1) becomes

$$\boldsymbol{Fdu} = \boldsymbol{J_{IC}\ dA} + \boldsymbol{P\ du} \qquad (5)$$

This equation demonstrates that the work done is to slit the bonds between meat tissues (fracture resistance) and overcome friction caused by the clamp between the knife's sides and the surrounding fat tissues. The deformation around the blade (**d**Δ) is negligible at this stage and can be disregarded. The force required to propagate the crack and overcome the fracture resistance depends on factors such as the crack's area (depth and width) and the local stiffness of the material. The force levels in these areas remain more stable as long as the knife does not encounter interfaces or air gaps. Figure 23 shows the case of cutting through meat tissues after penetrating the first interface.

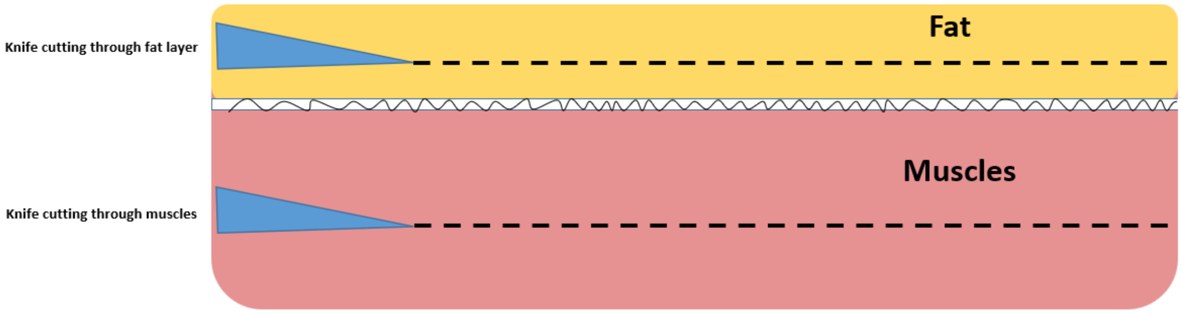


Figure 23: Knife cutting through meat tissues

Following an interface also exhibits stable and low force levels, as the bonds between the tissues are much weaker. These low force levels can be maintained unless the knife crosses an interface and cuts through it (Figure 24). When the knife is cutting towards the interface leading to the natural pathway between tissues, the force required for cutting increases because of the interface or the gap between the tissue layers at this region. Consequently, the deformation force must be added to Equation 5, which then becomes:

$$\boldsymbol{Fdu} = \boldsymbol{J_{IC}}\ \boldsymbol{dA} + \boldsymbol{P}\ \boldsymbol{du} + \boldsymbol{d}\Delta \qquad (5)$$

As mentioned earlier, in this case, the side forces are used to guide the knife to follow this interface and to maintain stable and minimum force transients on the tip of the knife.

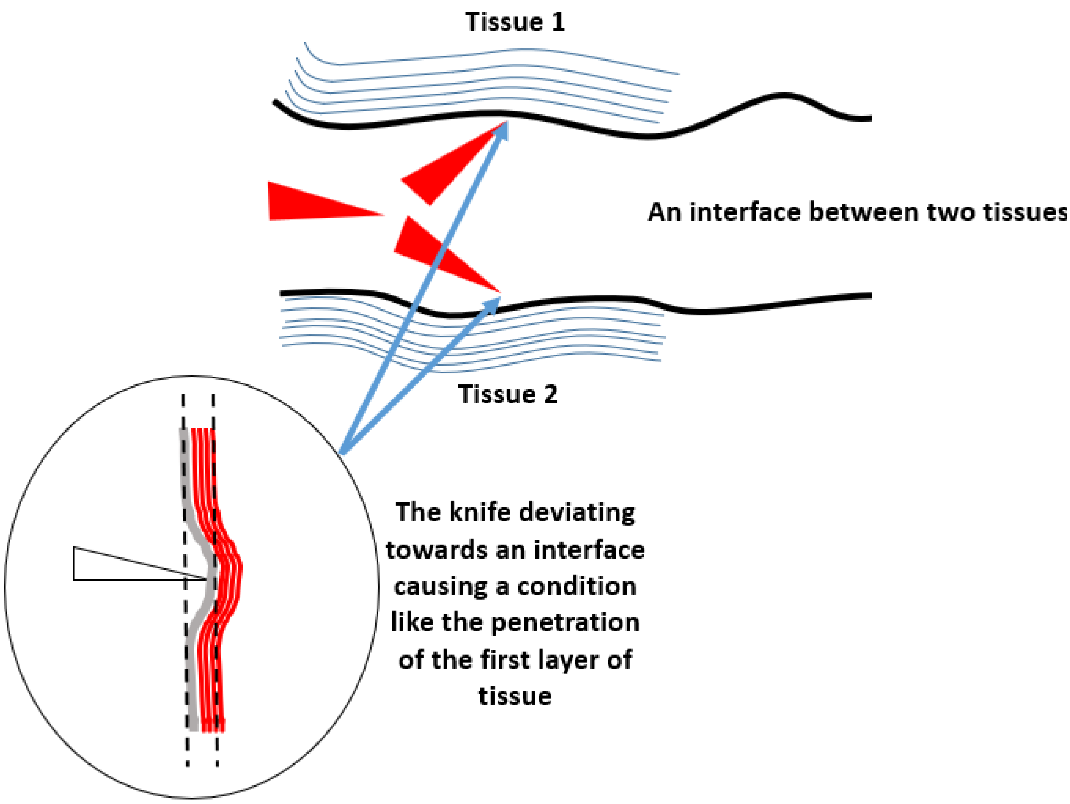


Figure 24: A representation of a knife attempting to follow an interface

The following chapter will examine the feasibility of using tactile sensing to guide a knife. It will focus on discriminating key features in red meat tissues and locating the knife's position relative to these features (Experiment 1).

CHAPTER 4

4.1. PAPER 2 - TACTILE SENSING FOR TISSUE DISCRIMINATION IN ROBOTIC MEAT CUTTING: A FEASIBILITY STUDY

4.1.1. Introduction

This paper demonstrates the feasibility of a tactile sensing-based approach for guiding a knife in cutting red meat tissues. The method utilises force data from a sensor attached to a knife to discriminate between various red meat tissues and their interfaces. The unique transients in the force data are identified and then correlated with the knife's cutting movements to precisely locate its position relative to meat features. The cutting task is segmented into critical stages, informed by the characteristics identified along the knife's trajectory. As an initial step in validating this technique, the study focuses on performing simple, straight-line cuts across different tissues under controlled experimental conditions and within a well-defined observable setup.

4.1.2. Published paper

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Tactile sensing for tissue discrimination in robotic meat cutting: A feasibility study

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ABSTRACT

This investigation explores an approach for tactile sensing to guide a knife attached to a robot to cut red meat. During cutting, the discrimination of tissue types and the approach to tissue interfaces is an important factor in this variable, deforming medium. Using a force sensor attached to a standard knife controlled by a 6-axis robotic manipulator, cuts were performed to a depth of approximately 20 mm across striploin chops. Force patterns showed significant similarity in cross-correlation analysis, with an 80–97% correlation coefficient. The force sensor reading exhibited identifiable patterns that could be tracked to pinpoint critical stages of the cutting process, validating the potential of tactile sensing in meat processing. The insights gained will facilitate the development of automated perception and corrective actuation strategies for maintaining the knife on the desired cutting path relative to tissue interfaces, adapting to the deformable nature of the meat in real-time.

1. Introduction

The red meat processing industry is a major contributor to the Australian economy. Locally, the industry is responsible for employing over 400,000 employees directly and through associated businesses (Meat & Livestock Australia, 2020; EY Building a Better World, 2017). Australia is globally recognised as one of the leading exporters of high-quality red meat products (Meat & Livestock Australia, 2020). Nonetheless, the industry grapples with hurdles in price-sensitive markets as Australia's labour expenses rank among the highest compared to other red meat exporting countries (Ruberg, 2021; Heilbron et al., 2018). Furthermore, the hazardous work environment and the exhausting tasks demand processors to allocate funds for work-related health issues and potential injuries, which are very common in the industry (Purnell, 2013). Strict hygiene standards and procedures are also indispensable to ensure that human-meat interaction doesn't compromise food safety by introducing bacteria or pathogens.

The incorporation of robotics in this sector has the potential to address these issues, improving health and safety conditions in abattoirs while enhancing profitability without negatively impacting product quality or inflating prices. The successful integration of robotics in the pork processing sector showcases the potential benefits the red meat processing industry could reap, as the two sectors share similar operational aspects. For instance, the Danish pig slaughter industry has recorded improvements in work environment health and safety, along with increased production, without compromising the quality of the final product (Hinrichsen, 2010). While pig, cattle and sheep carcasses share structural similarities, the softer and more fluid properties of pig tissues make the conventional preoperative sensing techniques to guide a blade along a pre-determined cutting path an applicable approach as the tissues deform less (Kauffman et al., 2001; Khodabandehloo, 2018). This distinction was highlighted in a study by Khodabandehloo et al. (Khodabandehloo, 2018), where attempts to employ the ALTD-450 pork automatic trimmer on beef striploin proved unsuccessful. The red meat tissues showed more deformation response and heavily variable fat thickness distribution across the product, requiring the knife to constantly adapt during cutting.

While the adoption of robotics in the deboning room is envisioned as a transformative measure for the industry, the unique characteristics of red meat create intricate obstacles to automation. Recent reviews thoroughly elucidate the engineering aspects and physical properties of red meat that influence the application of robotics and automation within the sector (Aly et al., 2023a; Romanov et al., 2022). Red meat, being non-rigid and highly variable in nature, presents a set of

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challenges for automation. The input products are characterised by unknown, non-uniform structures, varying sizes, and randomly distributed tissues (Toldrá and Leo, 2006). Additionally, carcasses undergo constant shape alterations owing to tissue relaxation over time (Choi et al., 2013; Nabil et al., 2015). The unpredictable response of tissues during disassembly when exposed to cutting forces adds to the complexity, as the products comprise fats, muscles, bones, and connective tissues, each contributing to diverse stiffness levels leading to a broad spectrum of rheological parameters (Nabil et al., 2015). These factors not only influence additional aspects, such as carcass gripping and the selection of an appropriate cutting tool, but also highlight the unreliability of pre-operation data and simulation models for guiding the cutting blade. Instead, these challenges underscore the necessity for real-time adjustments during the process.

The complex properties of red meat causes the absence of commercially available robotic systems specifically for beef cutting in the deboning rooms (Aly et al., 2023a; Kim et al., 2023). While lamb cutting lacks automation in abattoirs, a few successful applications have been made possible due to the smaller carcass size. Scott Automation has developed the only available automated boning room for lamb cutting, capable of producing primal cuts and portioning the forequarter and middle parts of the lamb carcass (Scott Technology Limited). This system relies on simple straight-line trajectories for the cutting blade, guided by an X-ray vision system and 3D vision cameras to determine the carcass's unique features (Scott Technology Limited, 2022a, 2022b). Initially, the deboning room was designed with a hindquarter processing system guided by force sensing for a more intricate cutting path around the lamb's aitch bone. However, this system did not reach the market due to its inability to meet the yield requirements for the final product (Maunsell and Scott, 2018).

Purnell et al. (Purnell and Brown, 2004) made an attempt to trim lamb chops using a system that harnessed the malleable properties of the meat. The system reshaped the trimming path by exerting focused pressure from the fat layer side to create a more uniform and predictable trajectory. Another system focused on separating the main muscle groups of a high-value cut in the cattle (beef round) (Nabil et al., 2015). It incorporated simulation attempts to anticipate the behaviour of the cutting trajectory and the local muscle tissues around it while vision cameras actively update the system with the current state of the workpiece (Nabil et al., 2015; Long et al., 2014). Simultaneously, a force control attached to a pulling robot stretches the connective tissues between the muscles and opens the path in front of the cutting blade (Nabil et al., 2015). Also, a system was attempted for beef quartering, using both vision (structured light image) and tactile (force sensing) perceptions to separate hindquarter and forequarter (Guire et al., 2010). The blade followed three straight cutting trajectories shaped as the letter Z guided by the rib cage and backbone profiles. To date, all the commercial robotic systems in red meat and pork processing can only perform the types of cuts with straight cutting paths that require minimum to no real-time adaptability.

A successful robotic system for red meat cutting can be envisioned to mimic the techniques and skills of a manual operator in the deboning room. This system should perceive and interpret essential product data, respond adaptively to changes in cutting conditions, and perform the most efficient cuts in real-time. Recent reviews assessed prevalent sensing technologies in existing automation systems, including X-rays, optical probes, ultrasonic sensors, vision cameras, and tactile sensing for real-time perception during cutting, and identified that optical probes and tactile sensing are ideal candidate technologies for further experimental research (Aly et al., 2023a; Mason et al., 2022).

The nature of cutting operations performed in abattoirs rely heavily on the physical interaction between the cutting tool and the carcass suggesting tactile sensing is a dominant perception modality in cutting. It identifies properties and behaviour in response, such as material stiffness and deflections (Luo et al., 2017). Valuable information can be extracted from tactile feedback if signal data is interpreted correctly (Dario et al., 1988). This claim is supported by the observation and analysis of skilled operators in the deboning rooms and their reliance on touch sense to locate and guide the knife relative to surrounding tissues and tissue interfaces. However, implementing force control to follow a complex cutting trajectory in a robotic system requires an alternative approach to force value alone. An alternative approach is needed in the application to more fully interpret the feedback signal in real-time (Aly et al., 2023b).

This paper reports on a fundamental study on the potential application of a tactile perception technique able to guide cutting in red meat. The study focuses on two primary objectives. Firstly, to demonstrate the practicality and sensitivity of tactile signals in identifying key features during the cutting process. Second, to establish correlation between the features and distinctive force transients captured using a force sensor.

The complexities involved in red meat cutting suggest a simplified approach to determine the most responsive cutting strategy. Cutting samples were prepared to enable '2D cutting' with consistent tissue presentation and responsiveness across the specimen. Constraining the cuts to 2D provided an experimental advantage in known tissue features within the medium and quantifiable, observable meat response. Also, a single-axis force vector sensor was enough to determine the reactive force transients on the knife.

While the experiment does not replicate real-market cuts, it serves to explore the capability of tactile sensing to differentiate and characterise various features of red meat tissue under controlled conditions. This research forms part of a broader investigation into interpreting the tactile data to formulate judgement and strategy to execute required tasks by cutting relative to meat tissues and tissue interfaces. The findings from this study can contribute to the development of robotic systems capable of real-time anticipation and response to the specific nature of red meat products and facilitate the automation of process cutting operations.

The scope of work encompasses a strategy to apply tactile sensory information that will augment automated machine real-time perception in cutting processes within meat tissues. Responding to deformation and the presence of critical structures and other phenomena are required in a cutting strategy when processing high value beef cuts to the required precision.

1.1. Tactile sensing and medium discrimination

Tactile perception involves obtaining force information through physical interaction with the surrounding environment. The technology goal is to detect the mechanical properties and responses of the operating mediums through force feedback (Luo et al., 2017). When interacting with various objects, the force transients provided through these encounters can offer insightful data if carefully observed and correctly interpreted.

Similar to red meat processing, surgical medical procedures occur in deformable non-uniform mediums. Tactile-based assistive robotic technologies have succeeded in the medical field, providing surgeons with critical information unperceivable by human senses. This adds a degree of precision and stability to the surgical instruments. The perception techniques take advantage of unique cues from the tactile signals to identify the cutting mediums and locate the position of the cutting tool relative to the surrounding tissue and tissue interfaces.

The epidural procedure is an example that has benefited from tissue discrimination via tactile perception to reach the epidural cavity and apply anaesthetic guided by force feedback (Brett et al., 1997). Fig. 1 (a) shows the trajectory of the needle and the tissues encountered during the procedure. The force data was used to discriminate the tissues and locate the depth of the needle relative to the interfaces. The trajectory was divided into four areas represented by notable changes in forces shown in Fig. 1(b). The elastic and viscoelastic properties of the tissues caused the deformation of the tissues around the needle tip, increasing the resistive forces before the needle successfully penetrates the first

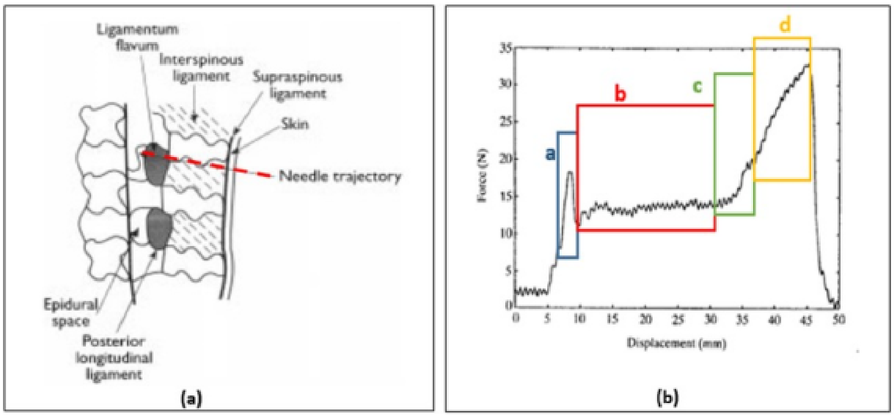


Fig. 1. a) The needle path during the epidural procedure is grouped into types of tissues needle encounters during each stage (Brett et al., 1997), b) The unique force transients during each stage of the epidural procedure (Brett et al., 1997).

interface of tissue or breaks through the last layer of tissue (regions a & d). Region b shows a more steady profile of forces while the tissues around the needle relax, with the friction between the needle and the tissues being the dominant force. The fatty tissues in region c show a moderate build-up in the resistive forces proportional to the needle length due to its viscous fluid properties. It can be observed that the dominant trends in the force profile explain the needle actions. The absolute values of the force varied between cuts, but the trends consistently showed the separate stages of the insertion.

The experiment in this paper explores a similar interpretation approach of tactile sensing, identifying the unique force transients and the sensitivity of forces corresponding with certain conditions or parameters while cutting across various tissues and tissue interfaces of red meat. The identifiable trends of forces could aid in the discrimination and prediction of features within the time-series sensory data, establishing a correlation with surrounding meat mediums and conditions.

The interpretation of the force data is based on knowledge of the anatomical structure of the test sample. As any red meat carcass primarily consists of bones, fats, muscles, and connective tissue, all cuts from a carcass can be divided into four groups concerning the mediums involved. These include muscle separation, deboning, trimming, and joint separation. The analysis of professional operators cutting showed that any cutting process could be divided into stages based on two consistent cutting actions performed across any task.

1) **Interface penetration:** this includes penetrating the first interface at the start of a cut, breaking through the last layer of tissue indicating the end of a cut and cutting through the connective tissue that separates any two mediums. These interfaces mark the transition of the blade from one medium to another.
2) **Interface following:** cutting through a medium with similar mechanical characteristics relative to an interface. This could be following the interface line between two mediums to separate them or to cut through a medium parallel to an interface line.

In the experiment, the author first established the cutting trajectory and monitored the different tissues and interfaces encountered by the knife. Then, the cut was divided into stages where the knife performed one of the above mentioned actions. Finally, the tactile feedback represented by force applied on the blade in the direction of the cut was examined for features and events that were correlated with sensory data transients.

2. Methodology

2.1. Equipment

The testing setup was constructed to perform the cuts using an ABB IRB 1200 manipulator with 6-axis movement capability mounted on a moveable cabinet. An adjustable table was attached to the front of the cabinet to hold meat samples. Two 90° stainless steel corners were fixed to the table using G-clamp to hold the test sample against the blade. The rig was developed to be food-grade and IP67-rated to ensure that all components were dustproof and waterproof to be regularly cleaned. The setup of the rig is illustrated in Fig. 2.

The experimental procedure was documented through Sony FDR-X3000 action cameras, with two devices strategically set at distinct angles. This arrangement aimed to capture a comprehensive visual record of the knife's position and the behavioural response of the test sample during the cutting process.

A knife blade was stripped of its handle and secured to a customised bracket. The bracket was attached to a 6-axis ABB force sensor 165, and both were attached to the robot arm manipulator. This sensor has a maximum threshold of 165 N in both the X and Y axes, and 495 N in the Z direction (ABB, 2015).

The force sensor integrated into this setup relies on the principles of strain gauge technology, a commonly adopted approach in robotic systems. Essentially, a strain gauge force sensor operates by detecting the deformation or strain of a material as force is exerted upon it. This deformation subsequently alters the electrical resistance of the material, a change that can be measured and used to calculate the applied force. Multiple strain gauge resistors are deployed in tandem to detect forces applied across different axes.

The combination of data captured by the sensor and the video footage from the camera enabled the derivation of a force-time series during the execution of the cutting process. This data can be correlated with the properties of the tissue and the reaction during cutting, offering deeper insight into the mechanics encountered.

2.2. Test sample preparation and structure

A piece of meat prepared from Striploin beef primary cut will be used as the test sample for the experiment. A typical beef striploin product contains two mediums, muscles covered with layers of fats and connective tissues between them (UNECE, 2004). The Striploin primary

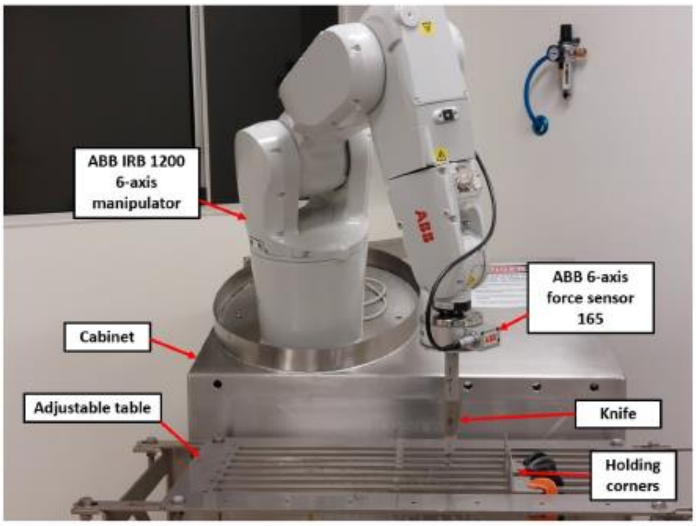


Fig. 2. Test rig setup.

piece is divided into smaller slices that are easier to manipulate. Fig. 3(a) shows the original product provided by an abattoir and a test sample prepared from it. The fat medium (subcutaneous fat) is structured in layers on the top of muscle tissues, with air gaps in between. The muscle medium consists of groups of muscles separated by a sheath of intermuscular fats. Each muscle is broken down into smaller bundles of muscle fibres (meat grain) enveloped in connective tissue made of collagen called Perimysium with intramuscular fats embedded in them (see Fig. 3(b)) (Megías et al.). Sample temperature was maintained at approximately 9 °C, to imitate the environmental conditions in an abattoir. The test sample was preserved, kept wrapped in the laboratory fridge, and removed when the experiment preparations were ready.

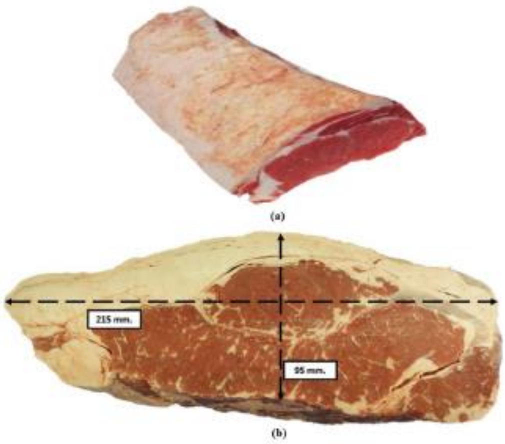


Fig. 3. a) Primary unprocessed striploin product b) Typical measurements of a striploin chop.

2.3. Experiment procedures

Prior to the experiment, crucial preparatory steps were executed, including load identification and force sensor calibration. The load identification was carried out by executing an internal load identification routine program via the robot. This routine was programmed to identify the items mounted on the robot's end effector encompassing the force sensor, knife bracket, and knife. The identification process computed and stored pertinent parameters, including the weight, dimensions, inertia, and tool centre point of the attached knife. The force sensor was calibrated to focus solely on detecting contact forces, thereby eliminating influence from gravitational forces. The knife motion was constrained to axial feed, and the reactive forces in the X-axis direction are the significant component on the knife blade in the direction of movement.

The robot was programmed to guide the knife along a predetermined cutting path perpendicular to the test sample plane, with an internal timer set into motion at the onset of the cutting process. After each experimental iteration, the robot stored the knife coordinates, the timer readings from when the knife initiated movement and their corresponding force readings. The knife took approximately 9 s to complete a test run from its starting position, during which force readings were gathered at a frequency of 1333.3 per second, yielding approximately 12,000 readings.

The setup shown in Fig. 4 was designed to investigate the cutting actions and the associated phenomenon while performing a simple straight-line cut through the different tissues of red meat. The first step was determining the cutting path on the workpiece and identifying the tissue's features along that path. After that, the knife was positioned vertically to the surface of the test sample and aligned with the cutting path, ready to perform the cut. The feed velocity of the knife is kept low and fixed at 20 mm/s to have better control over the behaviour of the sample. The depth of the cut was chosen to be approximately 20 mm from the upper surface. Cutting any deeper showed meat compression around the knife that saturated the force sensor as oscillating the knife was not part of the experiment. On the other hand, shallower depth than 20 mm could potentially cause the knife to miss part of the cut (especially the muscles) where the tissues are likely to relax.

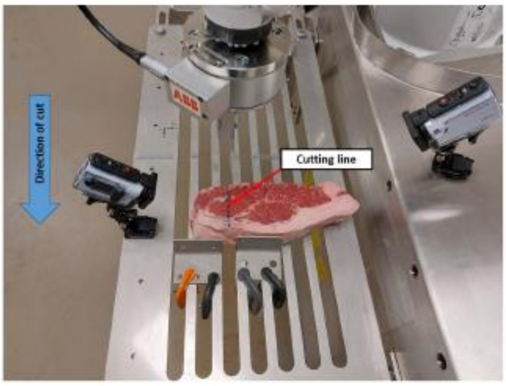


Fig. 4. Experiment setup.

Despite efforts to maintain a consistent depth throughout the cut, it should be noted that cutting through muscles always resulted in a slightly shallower depth compared to the fat layer. This discrepancy arises from meat deformation and relaxation over time, affecting knife penetration depth.

In order to align the knife's location in the test sample with the force readings, the timer of the recorded videos was synchronised with the robot's internal timer. The captured videos of the cutting process were trimmed to commence precisely when the knife began to move, marking the start of the robot's internal timer. As a result, the beginning of the edited videos coincided with the robot internal timer. This synchronisation allowed timestamps to be reliably correlated between cutting actions depicted in the videos with force transient data output by the force sensor.

3. Results and observations

This section outlines the findings and discusses the observations obtained from the experiment. Experimental cuts were conducted with a specific purpose – to observe and identify the unique transients in the tactile feedback, which can be utilised to discriminate between cutting mediums and events, and preemptively adapt to them. Notably, despite the heterogeneity found within red meat carcasses, consistent inherent traits of red meat exist which can effectively guide a cutting tool.

The initial defining feature is at tissue interfaces. These can be identified at the layers separating different mediums, where the knife penetrates to transition from one medium to the next. Depending on the cutting direction, such transitions may be from air to muscle, muscle to fat, or fat to air. These interfaces can be seen in Fig. 5 (a). Other significant features relate to the specific type of tissue being cut and its inherent characteristics. This is presented by intramuscular fats among muscle groups and air gaps within the fat layer, as illustrated in Fig. 5 (b). Identifying these elements contributes to our understanding of the knife's actions in relation to these features. The experiment tests the sensitivity and precision of tactile perception to distinguish these features and to indicate knife action and the reactive behaviour of the meat in response to applied force at the cutting stages.

Cutting tests were conducted 18 times, divided between the four sides of two pieces of striploin chops. The direction of 9 of these tests were executed starting from the muscles side towards the fat layer and the remaining tests were performed in the opposite direction from the fat layer side towards the muscles. The robot captured the forces, relative displacement, and time data in.csv format. MATLAB was employed for processing this data.

A cross-correlation analysis of the collected data was performed to determine the presence of patterns and commonalities in the force profiles generated across different tissues. To ensure accurate computations, interpolation was performed to align the length of the compared data sets. This analysis offered a means to quantify the level of similarity between various sets of time series data. The cross-correlation coefficient obtained from the cross-correlation analysis is between 1 and -1. The value of the number indicates the strength and direction of the relationship between two data sets. A correlation coefficient closer to 1 indicates a strong positive correlation, meaning that as values in one data set increase, values in the other data set also tend to increase.

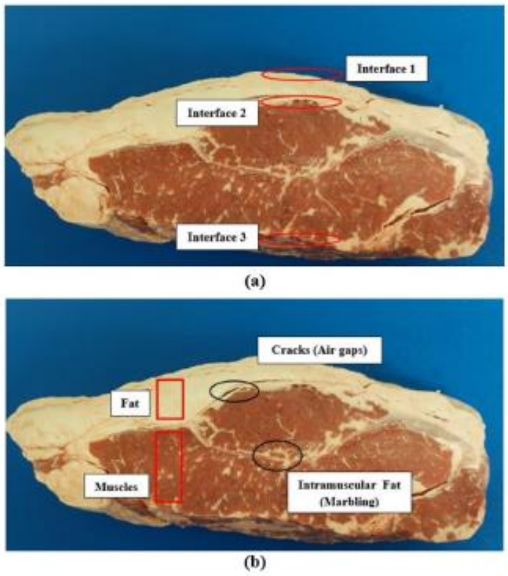


Fig. 5. a) The main interface during the cut, b) Features of fat and muscles.

Cross-correlation coefficients between force value datasets for cuts made in the same direction are presented in Table 1 & Table 2. Each table element shows the number of the cross-correlation coefficients between the cuts in the main row and column. For example, the cross-correlation coefficient between cut 1 and cut 2 is 0.96758. The results indicate a strong cross-correlation among all cuts in the same direction. Even the lowest coefficient, approximately 0.8, demonstrates a significant degree of similarity between the data.

The effective forces in this experiment were explained in the highlight of Khadem et al. (2016) and Okamura et al. (2004) work due to the resemblance in the cutting mediums similar to red meat. The reactive force on a needle penetrating tissues can be described as the sum of contributory force components: puncturing, cutting, friction and deformation force components. The puncturing force component is present when the knife is penetrating an interface. The elastic properties of the tissues result in deformation around the blade tip while penetrating an interface. The friction component acts tangentially along the blade surface inside the test sample, and is attributed to coulomb friction, tissue adhesion and damping (viscosity) effects. These resist motion of the knife. The cutting force component is encountered in slitting tissues and in opening the cutting path in response to the knife displacement. These three force components are combined at any given time during the cut and can be applied to discriminate knife interaction with tissue types and tissue interfaces.

Table 1
Cross-correlation coefficients between the forces obtained from each data set for each cut with the direction from the meat side to fat.

	Meat to Fat							
	Cut 2	Cut 3	Cut 4	Cut 5	Cut 6	Cut 7	Cut 8	Cut 9
Cut 1	0.96758	0.79507	0.87432	0.95543	0.97476	0.9292	0.9018	0.88642
Cut 2		0.82781	0.87273	0.96599	0.99385	0.89625	0.90756	0.89736
Cut 3			0.92947	0.87488	0.80977	0.90739	0.95104	0.90631
Cut 4				0.94641	0.87853	0.86038	0.93733	0.93436
Cut 5					0.97381	0.88133	0.93399	0.94779
Cut 6						0.89005	0.91285	0.9121
Cut 7							0.90434	0.8876
Cut 8								0.93562

Table 2
Cross-correlation coefficients between the forces obtained from each data set for each cut with the direction from the fat side to the muscles.

	Fat to Meat							
	Cut 2	Cut 3	Cut 4	Cut 5	Cut 6	Cut 7	Cut 8	Cut 9
Cut 1	0.93866	0.86403	0.83948	0.93197	0.92525	0.91649	0.87117	0.88506
Cut 2		0.89746	0.91614	0.92755	0.96912	0.94399	0.90528	0.93641
Cut 3			0.94338	0.93111	0.89622	0.91781	0.88691	0.89493
Cut 4				0.87892	0.86104	0.90626	0.87866	0.90842
Cut 5					0.96926	0.94471	0.89532	0.90633
Cut 6						0.95463	0.9129	0.92646
Cut 7							0.9502	0.97544
Cut 8								0.95348

3.1. Penetration of first interface

The robot initiates the cutting trajectory and the force readings are at their no-load values before contacting the first tissue layer. Upon the blade contact with the sample, whether from the muscle or the fat side, force is applied to the tissues compressing the meat sample against the stainless-steel bracket before penetration. The meat tissue deforms locally in the direction of the force. With increasing applied force, the tissues deform around the blade. When the mechanical limit of the contacting meat tissue layer is reached, the knife penetrates this tissue layer. The effective force of cutting through the first layer is the puncturing force that induces the limiting strain in tissue deformation. In contrast, the cutting and friction forces are negligible.

When cutting through muscle tissue, significant deformation occurs in the vicinity of the blade. This deformation causes tissue displacement of up to 50 mm, with an average displacement of 38 mm across all cuts, before the knife reaches the maximum force required for penetration at the first tissue interface.

In contrast, fat tissue exhibits rigidity, leading to minimal deformation and faster tissue breakdown. The tissue displacement observed in this case results from the pressure applied by the knife on the fat layer, which causes the meat to be compressed between the fat layer and the holding bracket, while the fat tissue itself undergoes minimal deformation.

Fig. 6 (a) showcases the deformation behaviour of muscles and fat tissues, highlighting their contrasting characteristics through visual examples from the experiment. Fig. 6 (b) plots illustrate the average force pattern of penetrating the first interface across all cuts for both muscle and fat scenarios. The force profiles display a positive gradient, indicating an upward slope, with the peak force value indicating the point at which tissue breakdown occurs. Notably, when cutting through muscle tissue, the force increase is slower before reaching the point of tissue breakdown compared to the penetration of fat tissue. Similarly, the force profile demonstrates a similar behaviour when the knife penetrates the intermediate interface between the fat and muscle tissues during the transition from one tissue to another.

3.1.1. Cutting through tissues

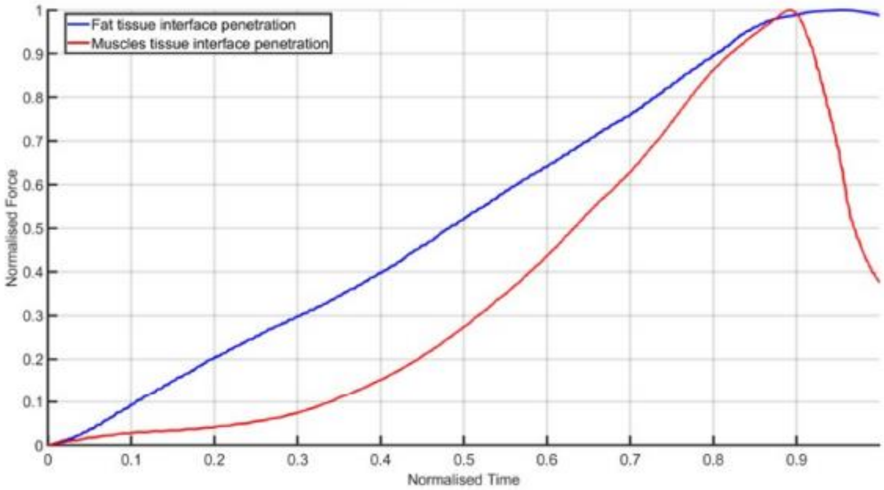
After penetrating the first layer of tissue and the knife enters the sample (regardless of the medium), the force values are sustained at the level needed for cutting the subsequent tissues. The effective forces switched from the puncturing force caused by meat deformation to the cutting and frictional forces. The dominant cutting force enables the knife to slice through tissues, surpassing the friction induced by clamping the sides of the knife and the surrounding tissues. Any sudden rise in the average force level is an indication of meat deformable behaviour to resist cutting through an intermediate interface or moving between tissue layers.

The two main tissue types in the test samples, muscle and fat, have varying force profiles in response to their internal mechanical properties, tissue characteristics and the direction of the cutting motion. Differential stiffnesses are the most prominent feature that can be used to discriminate between cutting through the two mediums. Muscles are more pliant and require less average force to cut. In some regions, thick intramuscular fat requires more force to cut through compared to the surrounding lean muscle tissue. The intramuscular fat resisted the blade's cutting movement, causing the sample to deform until cutting through. This leads to a sudden increase in force within the tissue due to the added deformation component of force. Cutting through fatty tissue yields a higher average force across the layer with more pronounced and steep fluctuations due to cracks and air gaps within the fatty tissue.

Fig. 7 exhibits the average force profile throughout a complete cutting run, encompassing all cuts while highlighting the two specific cutting areas: through the muscles and the fat layer. The graph demonstrates that as the knife cuts through lean muscles the force progresses smoothly with minor oscillations. In contrast, cutting through the fat layer is represented as a single force spike ending with the knife exiting the sample. This behaviour is attributed to the relatively small width of the fat layer observed across the majority of the samples. However, it is important to note that the width of the force representation of the fat area can vary depending on the width of the fat layer, which will be further illustrated through an example later in this section.

Table 3 presents the recorded forces while cutting fat and muscle tissues. It provides information on the maximum, minimum, and average force values observed in each tissue. While the primary focus of this paper revolves around force changes rather than the specific force values, the presented values offer insights into tissue structure and stiffness under experimental conditions. On average, cutting through

(a)



(b)

Fig. 6. a) An example from two cuts to visually show the differences in the deformation behaviour between the fat and the muscles, b) Average force profile and tissue behaviour when penetrating the first tissue interface of fat and muscles for all cuts.

muscles requires less force than cutting through fat tissues. The process of cutting through the fat layer displays higher changes due to the presence of air gaps. As the knife moves through these gaps, the sample deforms ahead of the knife at the corresponding tissue interface, resulting in a high spike in force.

3.1.2. *Cutting examples*

Fig. 8 shows a force profile of one of the cuts to provide valuable insight into the cutting process. It demonstrates the cutting path, the different stages undertaken by the knife, and the force profile generated by the force sensor throughout the cut. The cutting trajectory is segmented into the following.

1) **Stage 1:** This stage shows the penetration of the first interface and the tissue's deformation before the knife is entirely inside the test sample. It starts when the knife touches the test sample and ends when the blade is inside it.
2) **Stage 2:** In this stage, the knife cuts through the meat. The force graph displays a smoother progression, and the absence of sudden force spikes during the cut suggests the muscles are lean with minimal intramuscular fats. This stage starts when the blade successfully penetrates the first interface and ends when the blade touches the interface between the meat and the fat layer.
3) **Stage 3:** Represents the transition zone between the two primary tissues, where the knife cuts through the interface between the muscles and the fat. The force pattern exhibits a distinct shift between two levels of force readings. This stage starts when the blade touches the intermediate interface and ends when the blade is inside the fat layer.
4) **Stage 4:** This stage signifies cutting through the fat tissue. The force drop in the middle occurs due to the presence of a crack (air gap) in the fat layer, leading the knife to exit and then re-enter the fat layer. This stage starts when the blade is in the fat layer and ends when the blade begins breaking through the last layer of fat tissue.
5) **Stage 5:** In the final stage, the knife breaks through the final tissue interface before exiting the test specimen.

Force transients of Fig. 8 demonstrate the accuracy in timing between force sensor data transients and the observed internal dynamics of the cutting process. It shows the forces measured by the robot over time, while the black dots represent the timing of each stage as observed in the cutting video, documented in Table 4. Notably, there is a clear

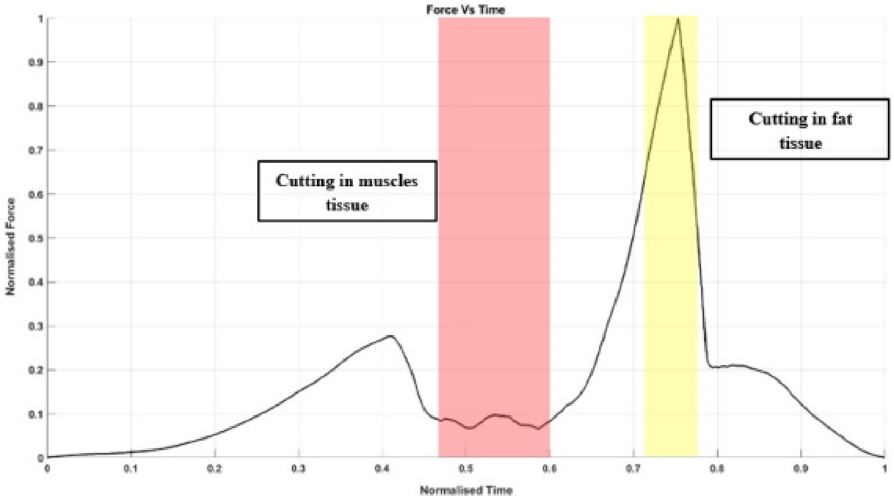


Fig. 7. The average force profile of all the cuts that start from the muscles side.

Table 3
The maximum, minimum and average forces while the knife is cutting through the muscle and fat tissues.

Cut	Muscles			Fat		
	Maximum Force	Minimum Force	Average Force	Maximum Force	Minimum Force	Average Force
1	13.2879	5.1322	7.5746	18.8389	8.2403	12.8430
2	10.1457	3.6465	6.5167	42.3090	11.8010	26.4718
3	9.6075	2.1111	5.0839	52.1601	8.5614	22.1972
4	14.6581	3.2740	6.5889	26.7857	5.3405	16.8765
5	5.4402	2.2938	3.8491	38.7624	8.9583	18.3905
6	6.1854	1.7559	3.3064	43.9371	11.4832	22.4884
7	9.2066	3.20445	4.9676	46.337	9.2046	23.6836
8	8.4619	1.9186	4.4853	31.3121	13.1382	18.9103
9	6.9716	1.9212	4.6965	32.9264	12.1866	18.7947
Total average	5.23 N.			20.07 N.		

correspondence between the observed transition points in the video, indicating the knife's movement from one stage to another, and distinct changes in the force profile.

Additionally, Fig. 9 and the accompanying Table 5 illustrate the same stages. However, here the cut starts from the other side, moving from the fat layer towards the muscles. This alternative perspective reinforces the consistency and reproducibility of the observed stages and their associated force profiles.

The results from the tactile feedback demonstrate a high level of precision across all the test samples. The force sensor successfully captures the nuances of the cutting process, providing accurate and reliable information about the internal dynamics of the tissue. These findings underscore the efficacy and reliability of the tactile feedback system in discerning different cutting stages and their corresponding force signatures.

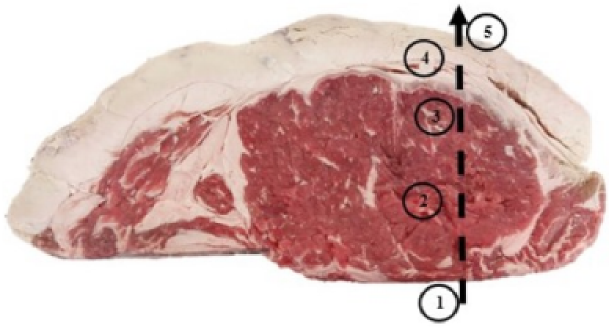
The findings of this section show that tactile perception effectively distinguishes between tissues and cutting stages close to the blade during a cutting procedure in experimental settings. We further propose to leverage the mechanical response of composite meat tissue structures as a predictive tool. This approach is crucial given the unpredictable and dynamic nature of the mechanical properties of these structures.

Our next aim is to develop a real-time control strategy that adjusts the cutting trajectory based on the tissue's location and response. This strategy would employ the characteristic features of the time-series data to align with crucial conditions. This predictive model could indicate when the knife is approaching a tissue interface, enabling application of evasive manoeuvres or oscillatory movements to facilitate cutting.

An effective yet straightforward approach, drawn from previous observations, is to monitor force gradients over a certain period. A persistently increasing gradient might suggest that the knife is encountering more resistance than usual, indicative of the sample deforming as the knife approaches an interface. Fig. 10 shows the force profile of 'Cut 1' after being smoothed to reduce the noise in the data using a moving average filter and the first gradient plot (first derivative). The cutting stages can be identified by observing key phenomena. For instance, during stage 2, the force gradient exhibits a smoother profile compared to cutting through the fat layer, which is characterised by sharp changes in stage 4. Also, during stage 3, a notable increase occurs when approaching the intermediate interface. These unique transients could be used to automatically identify the cutting stages.

4. Discussion

The results of this section show that tactile sensory information can be interpreted to discriminate different approaching tissues, interfaces and other inclusions in close proximity to the blade during a cutting process. This capability offers potential to cut meat relative to tissue interface position in real-time; an essential attribute when trimming



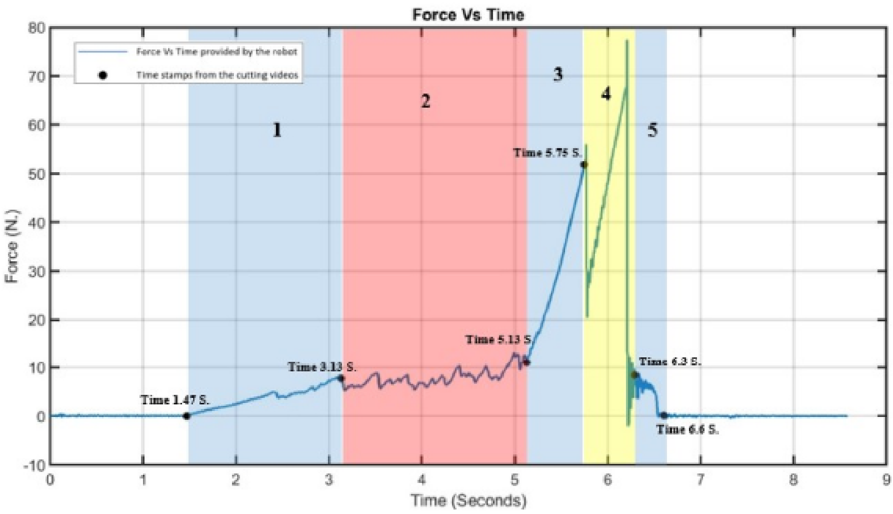


Fig. 8. The stages of cutting through the red meat tissues starting from the muscles side.

Table 4
The time interval of each cutting stage extracted from the cutting videos.

Time (seconds)	Cutting stages	Cutting action
1.47 to 3.49	Stage 1	Penetration of first interface
3.49 to 5.13	Stage 2	Cutting through the meat
5.13 to 5.75	Stage 3	Penetrating the interface between the lean and the fat layer
5.75 to 6.3	Stage 4	Cutting through the fat layer
6.29 to 6.6	Stage 5	Breaking through the last layer of tissue and leaving the sample
Total time = 5.13 s		

meat products and in tissue separation operations. The next stage in the research is to assemble a machine response with an appropriate change in cutting motion for the detected state in the process and meat workpiece.

Striploin trimming is the task of focus to be characterised in the highlight of tactile perception to perform the task by following the cutting path relative to the fat/lean interface. The trimming system is envisaged to include a vision system to initially scan the product and establish a cutting trajectory, while tactile perception ensures adherence to this trajectory, adjusting the blade in real time to task-related cutting incidents. For instance, detecting the deviation of the blade from the cutting path and re-aligning the cutter to stay on track relative to tissue positioning during the procedure. Blade deviation can be detected by measuring the net lateral forces, as the deviation is a result of the tissue deformation pushing the blade away from the correct cutting path. Fig. 11 shows an example of the effect of the fat layer structure and the deformation of the tissues on a knife trying to follow a predefined straight cutting path. The effective direction of the forces on the sides of the knife (blue arrows) indicates the direction of the deviation. The strategy encompasses the blade taking necessary measures to counteract deviating forces, ensuring it maintains a consistent force profile on the cutting equipment.

The work in tactile perception is building towards a successful implementation of robotics in the red meat industry in ways similar to those experienced by the pork industry. Similar operational results are expected, such as enhancing production efficiency, reducing operating costs and losses, and improving the overall quality of the end-product (Hinrichsen, 2010). The scope of this paper did not delve into key

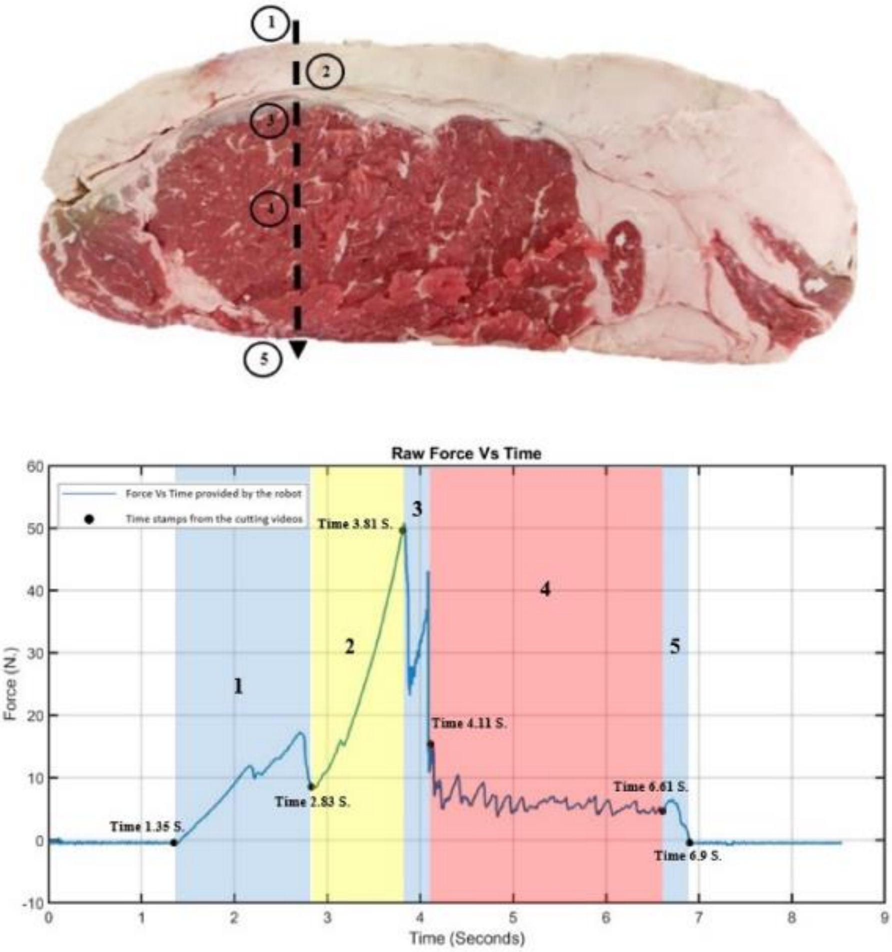


Fig. 9. The stages of cutting through the red meat tissues starting from the fat layer side.

Table 5
The time interval of each cutting stage extracted from the cutting videos.

Time (seconds)	Cutting stages	Cutting action
1.35 to 2.83	Stage 1	Penetration of first interface
2.83 to 3.81	Stage 2	Cutting through the fat layer
3.81 to 4.11	Stage 3	Penetrating the interface between the lean and the fat layer
4.11 to 6.61	Stage 4	Cutting through the meat
6.61 to 6.9	Stage 5	Breaking through the last layer of tissue and leaving the sample
Total time = 5.49 s		

considerations like process speed and end-product quality. However, once a successful control strategy is in place, these factors will be addressed. The focus will then shift from fundamental studies and proof of concept to developing a system more suited for the market.

5. Conclusion

This paper establishes an approach to interpret tactile sensing data transients as a guide for cutting beef using a knife deployed on a manipulator. The experimental design was inspired by the success of using tactile sensing in delicate medical procedures such as guiding surgical needles. The study has focused on examining tactile sensory data transients when executing a simple straight cut across different tissues in a preprepared striploin chop product and correlation between tissue features, tissue response and events. Through performing 18 cuts using a static knife attached to a robotic manipulator, the analysis of force transients to discriminate correlating patterns to features in the meat revealed similarity through cross-correlation analysis. Correlation coefficients ranging from 80% to 97% were found. Through synchronising and correlating cutting events in the cutting videos and the unique transients in forces, the force signal was shown to isolate identifiable features that can be used to discriminate tissues and tissue

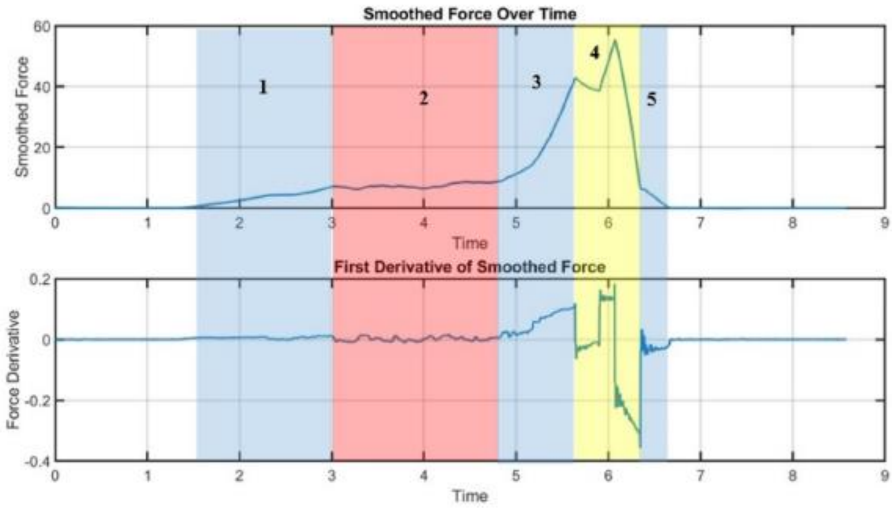


Fig. 10. Identifying tissue interfaces during cutting using gradient plot.

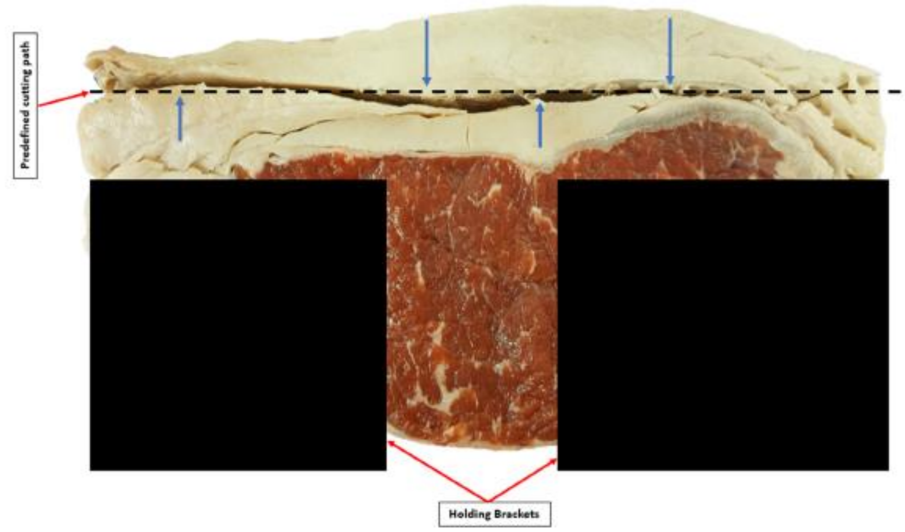


Fig. 11. The fat tissue structure and tissue deformation causing the knife to deviate from the predefined cutting path.

interfaces when cutting in an automatic process.

The findings have effectively demonstrated the potential of tactile sensing in meat processing and can be used to identify critical stages of the cutting process. This validation of tactile sensing opens opportunity to develop an automated perception and corrective actuation strategy. The approach can be used to maintain knife trajectory on the desired cutting path relative to tissue interfaces. The method prepares for real-time adaptation to the deformable nature of the meat.

Credit author statement

Basem Ade Aly: Conceptualization, Investigation, writing- original draft. Professor Peter Brett: Conceptualization, Tobias Low: Writing-review & editing. Derek Long: Writing-review & editing. Craig Bailie: Writing-review & editing.

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The University of Southern Queensland is involved in the research through the supervisory team to guide the author and ensure they meet the university requirements to complete their Ph.D. by publications.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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4.1.3. Links and implications

The study presented in 'Tactile Sensing for Tissue Discrimination in Robotic Meat Cutting: A Feasibility Study' highlights the capability of the proposed tactile perception approach to interpret the actions of a knife during meat cutting by distinguishing the behaviour and features of different tissues along the knife's path. The primary focus was on the force exerted on the knife's tip in the cutting direction. We visually validated this approach by observing the sensor's accuracy in capturing distinct force transient responses, which are specific force patterns in the data, related to various tissue features and behaviours. Furthermore, we conducted an analytical validation by demonstrating the consistency of these patterns in repeated cut by performing cross-correlation analysis on the collected data. The forthcoming Section 4.2 builds upon this experiment, using the same setup to investigate the impact of knife depth on cutting performance. This aspect is particularly challenging to control due to the inherent physical properties of meat tissues.

4.2. SENSITIVITY OF CUTTING FORCE TRANSIENTS TO THE DEPTH OF CUT

While efforts in Section 4.1 were made for a consistent cutting depth across all experiments, the inherent variable properties of meat tissues— stiffness, deformation, and external influences such as gravity and temperature—made this a challenge. This chapter determines the sensitivity of the nature of cutting force transients to cutting depth. Working with the same experimental setup as Section 4.1, the robot was used to cut samples of Striploin chops to varying depths.

4.2.1. Introduction

Cutting depth is an influencing factor on the effective cutting force, particularly when the knife penetrates the initial interface and continues cutting through the tissue. An increase in the cutting depth requires more compressive force and leads to greater contact between the sides of the knife and the surrounding tissues, causing increased friction.

Maintaining a constant cutting depth during manual operation is not possible in most situations. Process Operators are unable to visualise the interior of the meat, and depth is gauged by the changes perceived in reactive force detected as the knife progresses in the meat tissues using tactile sense when cutting with a knife. The complex structure of red meat, comprising various tissue types, presents differing impedance levels to the cutting knife. This variation in resistance can be detected along the knife's cutting trajectory.

Further judgement is applied by the operator, often accompanied by visual information as the meat workpiece will likely deflect, deform and then relax when responding to applied cutting forces. Judgement is complex, relating projected visualisation of the final product form combined with the knowledge of the presence of meat tissue structures within the workpiece. Using real-time sensory perception to estimate position, combined with high-level interpretation skills to form a representative perception, operators can achieve accurate cuts by identifying the events and phenomena related to the blade position and motion within the local surrounding tissues.

In the laboratory and during the experiments, the previously mentioned factors regarding the structure of the test samples and the nature of red meat tissues, along with occasional unavoidable errors while cutting the test samples, can cause slightly uneven samples. Moreover, meat deformation due to cutting forces results in inconsistent cutting depths between experiments. These variations underline the importance of understanding how depth affects force transients during cutting events. The experiment aims to determine how depth influences the ability to discriminate the unique force transients related to the tissues, their interfaces, and the overall product behaviour.

4.2.2. Results and Observations

Using striploin chop samples, cuts were performed at different depths from the surface of each sample. The knife tip was advanced into the tissue from the external surface of the sample on parallel cutting trajectories separated by known increments and was programmed to descend in the Z direction 10 mm lower sequentially between each trial cut. The three cutting depths were 10 mm, 20 mm and 30 mm. Two cutting trials were performed for each depth, resulting in a total of 6 trials. Representation of the cutting paths is shown in Figure 25. Table 8 presents the length of each cutting path divided between the length of the cut in the fat layer and muscles. The table also shows the pre-adjusted depth and the knife’s actual depth inside the sample measured using a stainless steel rule.

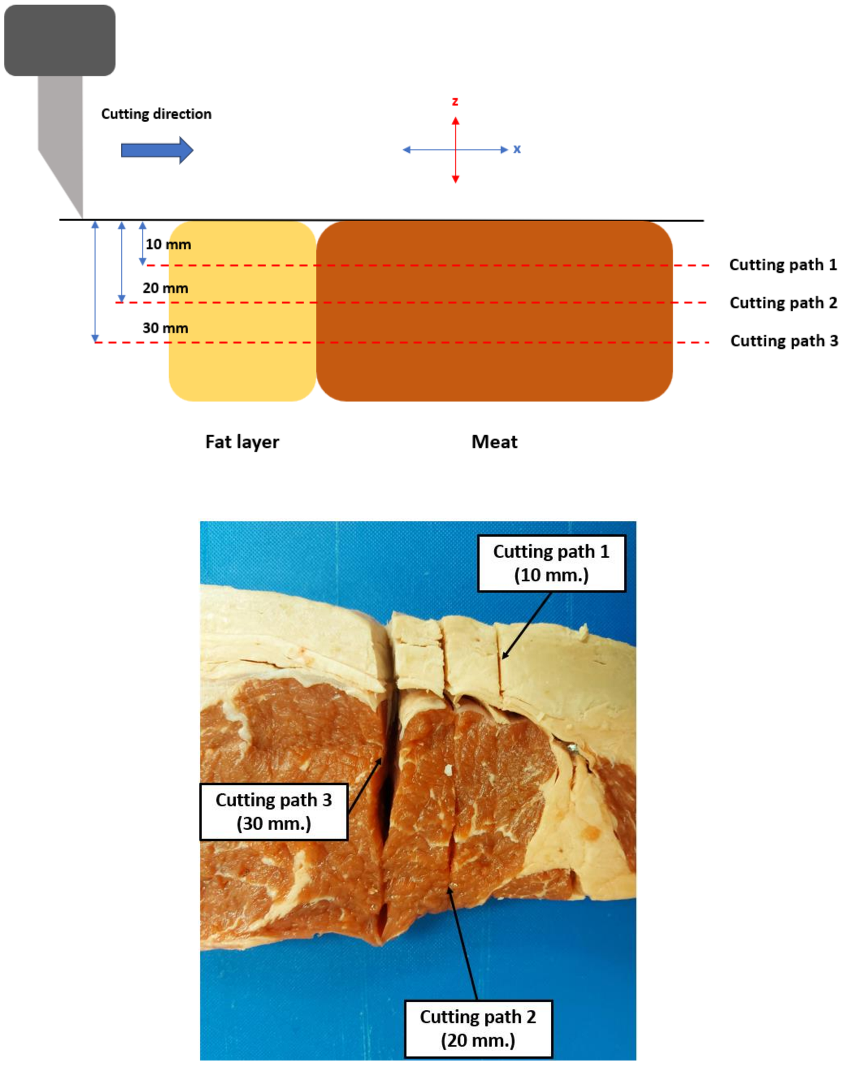


Figure 25: Representation of the cutting paths

Table 8: Measurements data

Data 1 **Pre-adjusted depth = 10 mm**	Length of fat layer = 25 mm.	Actual depth in fat = 5 mm
	Length of muscles = 59 mm.	Actual depth in muscles = 3 mm.
Data 2 **Pre-adjusted depth = 10 mm**	Length of fat layer = 19 mm.	Actual depth in fat = 9 mm.
	Length of muscles = 67 mm.	Actual depth in muscles = 3 mm.
Data 3 **Pre-adjusted depth = 20 mm**	Length of fat layer = 17 mm.	Actual depth in fat = 15 mm
	Length of muscles = 70 mm.	Actual depth in muscles = 11 mm.
Data 4 **Pre-adjusted depth = 20 mm**	Length of fat layer = 25 mm.	Actual depth in fat = 16 mm
	Length of muscles = 80 mm.	Actual depth in muscles = 12 mm.
Data 5 **Pre-adjusted depth = 30 mm**	Length of fat layer = 16 mm.	Actual depth in fat = 28 mm
	Length of muscles = 70 mm.	Actual depth in muscles = 24 mm.
Data 6 **Pre-adjusted depth = 30 mm**	Length of fat layer = 21 mm.	Actual depth in fat = 21 mm
	Length of muscles = 69 mm.	Actual depth in muscles = 20 mm.
Temperature = 8^{o} C		

Figure 26 shows detectable features within the tissues of the meat test sample. The cutting can be divided into five stages:

1- Penetration of the first interface.

2- Cutting through the fat layer.

3- Penetrating the intermediate interface between the muscles and the fat layer.

4- Cutting through the muscles.

5- Breaking through the last layer of tissue and leaving the sample.

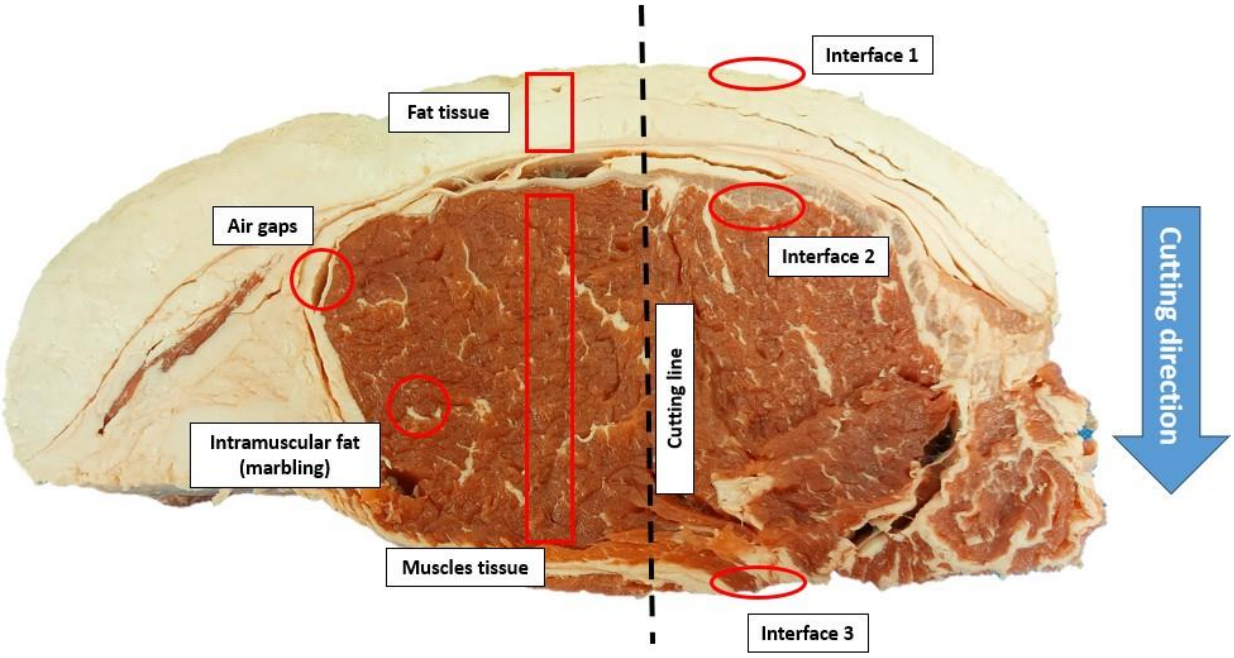


Figure 26: An example of a cutting line showing the direction of one cut and the structural features of the test sample

The precision in identifying the previously mentioned cutting stages based on the unique force transients for each cutting depth was evaluated by correlating the status of the cutting task with force data. This was done by synchronising the time recorded by the robot with the time stamps from the cutting videos. The correlation involved plotting the force-versus-time data (Figure 27) provided by the robot for each cut. The time stamps for each of the cutting stages were marked on the plot. These stages were represented by black dots on the graph and were observed from the video (refer to Table 9). Each cutting stage is colour coded and numbered and is a 'Correlating Time Stamp'.

Table 9: The timestamps of the different stages of cutting as measured and observed from the cutting videos

Data	Fat				Penetrating the interface between the fat and muscles (Sec.)		Muscles			
	Penetration of first fat tissue interface (Sec.)		Cutting through fat layer (Sec.)				Cutting through the muscles (Sec.)		Breaking through the last layer of tissue and leaving the sample (Sec.)	
1	2.23	2.7	2.7	3.89	3.89	4.26	4.26	6.46	6.46	7.0
2	1.96	3.04	3.04	3.79	3.79	4.33	4.33	6.43	6.43	7.13
3	1.93	3.13	3.13	4.23	4.23	4.96	4.96	6.46	6.46	7.2
4	1.39	3.06	3.06	4.29	4.29	5.29	5.29	6.6	6.6	7.5
5	1.3	2.76	3.23	4.31	4.31	4.86	4.86	6.7	6.7	7.38
6	1.46	3.29	3.29	4.43	4.43	5.03	5.03	6.43	6.43	7.7

First stage: The penetration of first tissue begins when the knife contacts the sample and ends when the full length of the blade is inside the fat layer. During this stage, two phenomena are observed. The first is the deformation of the first layer of tissue before the penetration. The second is the layer of fat responding to push and deform the muscle tissue beneath. Muscle tissues are more malleable than the fat, which is fixed using the holding brackets. This stage is characterised by gradually increasing forces until fat tissues reach their limiting mechanical stress and allow the blade inside the sample.

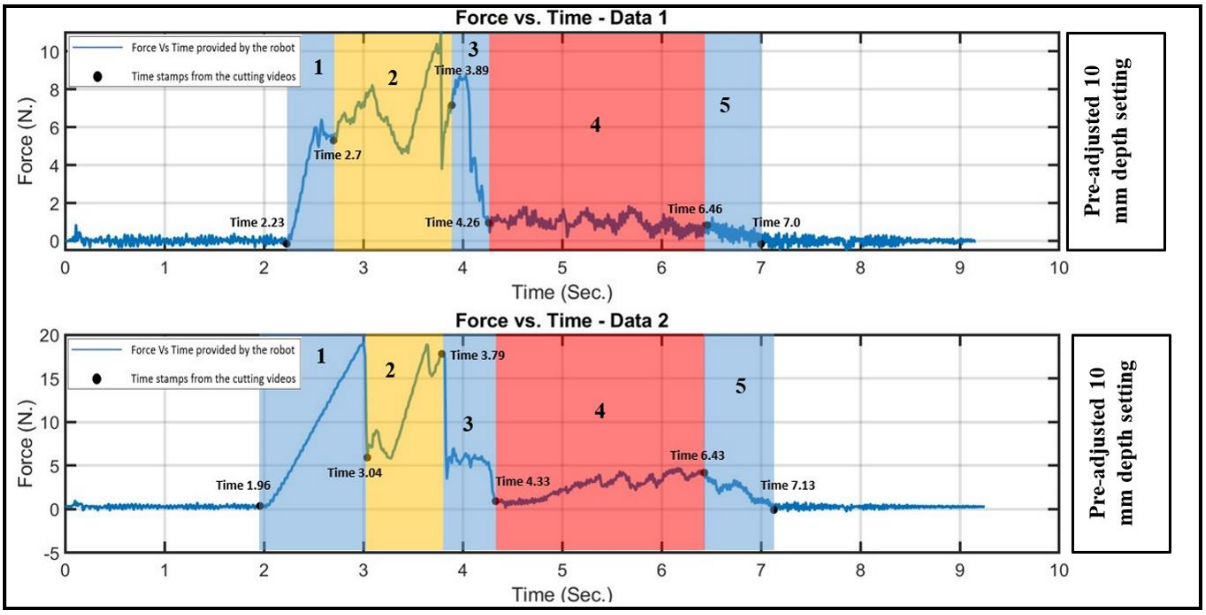
Second stage: Cutting through the fat tissues. The tissues are filled with cracks and air gaps, which cause spikes in force while the knife crosses the interfaces associated with these gaps.

Third stage: Cutting through the interface between the fat layer and the muscles. The interface is marked by a sinew that extends over the sample, varying in thickness in different areas. It is a transitional stage, where the knife moves from one cutting medium to another.

Fourth stage: Cutting through muscle tissue is represented by a lower average of the force values and more smooth transients punctuated by the small peaks associated with the knife crossing muscle fibrous tissue, which indicates leaner meat with less intramuscular fat between the muscle groups.

The final stage involves cutting through the last layer of tissue and exiting the sample. The force pattern decreases throughout this stage until it reaches the no-load force values. Intramuscular fat may present at the end of the cut, leading to a slight increase in force values just before the knife exits the sample.

The plotted data capture accurate and distinct variations in the force transients corresponding to the different cutting stages observed in the videos, regardless of the depth of the cuts. The distinction between the stages and the pattern similarity was affirmed and demonstrated statistically through cross-correlation analysis between the data sets. The data sets were normalised and the cross-correlation analysis was performed between each two data sets using MATLAB. Table 10 presents the resulting cross-correlation coefficients at 0 lag between each data set in the first column and first row. Since the data is normalised, coefficients are between -1 and 1. A coefficient of 1 indicates exact linear similarities between the data sets, -1 suggests inverse relation, and 0 shows no relation. The cross-correlation coefficients reveal high force pattern similarities across all the data sets, regardless of the cutting depth. The smallest coefficient is 0.8814, indicating over 88% similarity.



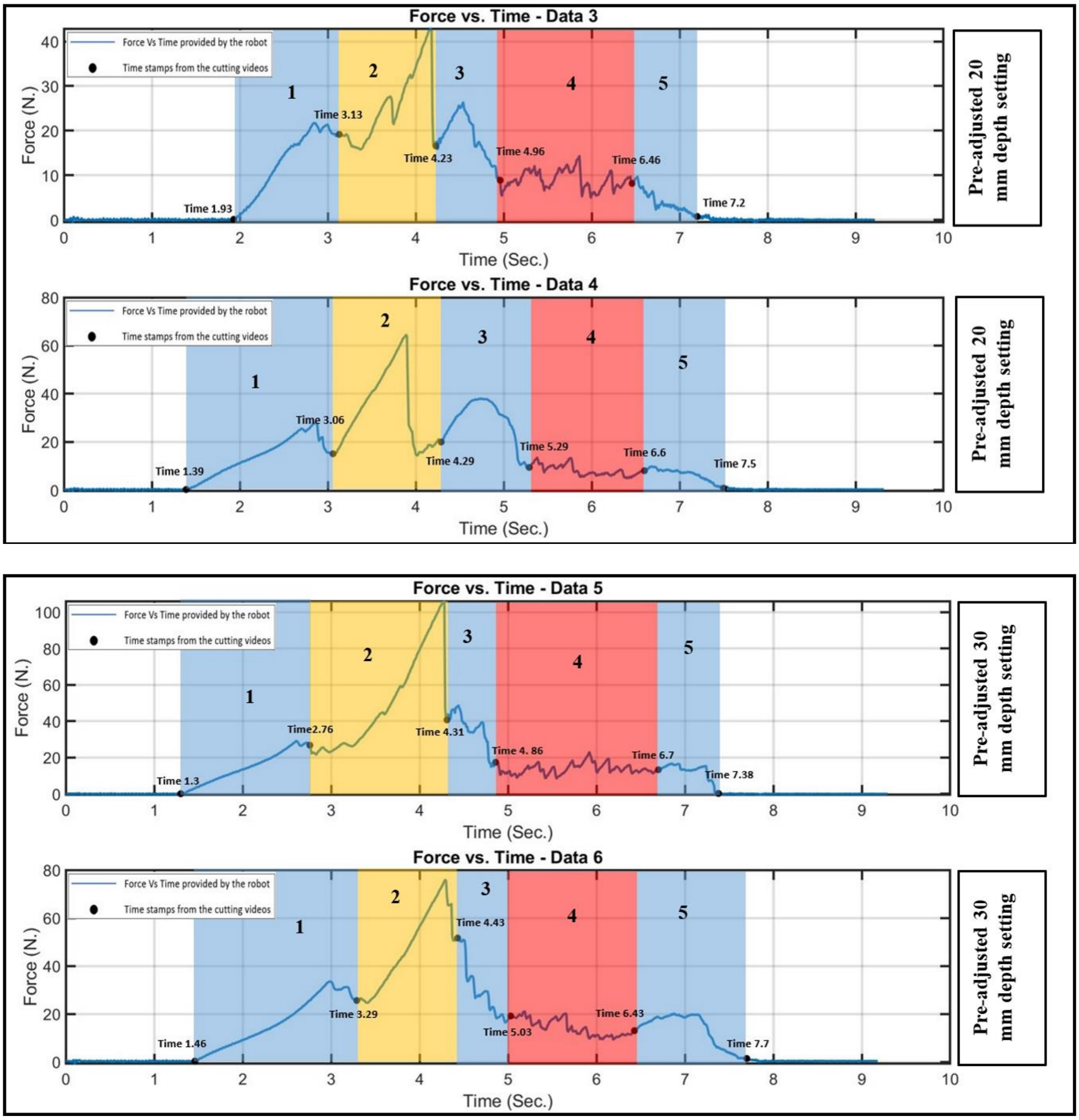


Figure 27: The stages of cutting through the red meat tissues starting from the fat layer side

Table 10: Cross-correlation coefficients between the forces obtained from each data set for each cut across the tissue interface from fat to muscle

Fat to Meat					
	Data 2	**Data 3**	**Data 4**	**Data 5**	**Data 6**
Data 1	0.94305	0.9114	0.87707	0.90488	0.91381
Data 2		0.89288	0.8814	0.88443	0.88459
Data 3			0.92721	0.95402	0.9262
Data 4				0.9021	0.92403
Data 5					0.97608

On the other hand, as anticipated, the change in depth affected the force required to perform the cut. The deeper the knife goes into the sample, the higher the average force values across the cut are. This is demonstrated in Table 11

Table 11: Maximum, minimum and average forces at each depth

Data	Fat			Muscles		
	Maximum Force	**Minimum Force**	**Average Force**	**Maximum Force**	**Minimum Force**	**Average Force**
1	11.0122	3.8086	6.8263	1.8328	0.08387	0.96786
2	18.8778	5.837	11.5177	4.6788	0.16601	2.6377
3	42.8863	15.7821	25.3095	14.293	4.9778	8.9352
4	64.4527	14.3995	33.0239	13.5371	4.9679	8.2061
5	106.023	21.5763	49.2839	22.9452	8.4549	13.8376
6	75.8358	24.6712	46.9735	21.071	9.2733	14.3082

4.2.3. Conclusion

The results have demonstrated that the depth of the knife in red meat tissues does not affect the capture of the characteristic force transients associated with the key cutting stages, which are defined relative to tissue types and interfaces. Visual observation of the data showed a precise and consistent correlation between the cutting stages and the unique force transients in the collected force data. Repetitive cutting tests at different depths yielded high cross-correlation coefficients, underscoring the consistency of the force data profile, provided the features remain unchanged. The effect of depth appeared in the magnitude of force values, not in the pattern, as evidenced by the average force values at the different stages of cutting. However, our experimental setup, which did not include oscillating movements for slicing tissues, revealed that deeper cuts might cause the meat to clamp around the knife, leading to increased resistance. This necessitates higher forces for cutting, potentially saturating the sensor's readings. Additionally, deeper cuts could cause displacement of the samples, as they are fixed to the cutting table. Therefore, while cutting depth does not inherently affect the force transients, which is the focus of the research, shallow cuts are recommended in our experimental setup to mitigate these issues. The next set of experiments in Chapter 5 extends the approach and applies it to the more practical cut of striploin trimming.

CHAPTER 5

5.1. PAPER 3 - ROBOTIC FAT TRIMMING: CHARACTERISATION OF RED MEAT TISSUE STRUCTURE USING TACTILE PERCEPTION

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ABSTRACT

This study investigates reactive force transients for discriminating meat tissues and guiding a robot when cutting beef. Using a 6-axis anthropomorphic robot manipulator with static knife and a 6-axis force sensor, cuts were performed relative to the principal meat tissue interface of striploin steak. Reactive force transients on the knife showed high correlation, mostly over 95%, confirmed by complementary analyses. The correlation diminished on approach to interfaces. Lateral force component exhibited sensitivity to the contour of the natural cutting path in close proximity to the tissue interface, whereas the orthogonal cutting axis force component discriminated knife entry onto this path. Applied to automatic trimming of striploin steak the results inform a novel real-time approach for tactile sensing in machine perception. Further exploration of the approach to automatic application in a trimming operation will serve to confirm levels of accuracy and robustness that can be achieved.

KEYWORDS

Tactile
Perception
Force sensor
Robot
Beef cutting

1. INTRODUCTION

The Australian red meat industry is a production leader of high-quality beef. While the industry is a significant contributor to Australian GDP, it is highly dependent on overseas labour for manual operations in meat production, as nationally the required skills are scarce. Both staff retention and national recruitment are exacerbated by the perceived near-freezing conditions and risks of the work environment, which do little to compete with working conditions in other industries

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(Romanov et al., 2022). The resulting production labour costs are the highest amongst international competition (SG Heilbron Economic & Policy Consulting, 2018).

Automation is anticipated as the industry solution, encouraged by the success and benefits reported in other industrial sectors (IFR International Federation of Robotics, 2021). However, the machine processing of meat workpieces, with the significant variations and the deformation of these natural mediums, requires high capability in machine perception, judgement, and adaptation to compete with exacting product specifications achieved by skilled human operators. Whether tasks involve separating meat tissues, slicing, or trimming to achieve finesse in high-value products, automation will need to respond to the presence of meat tissue interfaces, deflections and deformation induced by applied cutting forces. Near real-time machine perception will be needed to automatically determine corrective cutting trajectories and to maintain desired cutting paths relative to the tissue medium. Acceptable product presentation and yield are highly dependent on these factors.

Working toward this requirement, this paper reports research on a novel approach to tactile sensing able to discriminate and follow tissue interfaces during cutting operations. Tactile sense offers potential to discriminate the nature and behaviour of internal meat tissue structures at the point of cutting. This investigation on the search for a suitable tactile sensing approach for the task has focused on separating fat from lean tissue with defined proximity to the fat/lean tissue interface by using striploin steaks. In this form, the presentation of meat tissues is amenable to experimental verification of cutting relative to internal meat structures.

1.1. Description of the striploin trimming operation

Striploin is a valuable beef cut estimated to be 15% of carcass value. The cut extends between the rib cage and rump adjacent to the spine region covering from 0 to 3 ribs (Figure 1) (Standard, 2015). The dimensions and weight range are stated in Table 12 (Khodabandehloo, 2018).

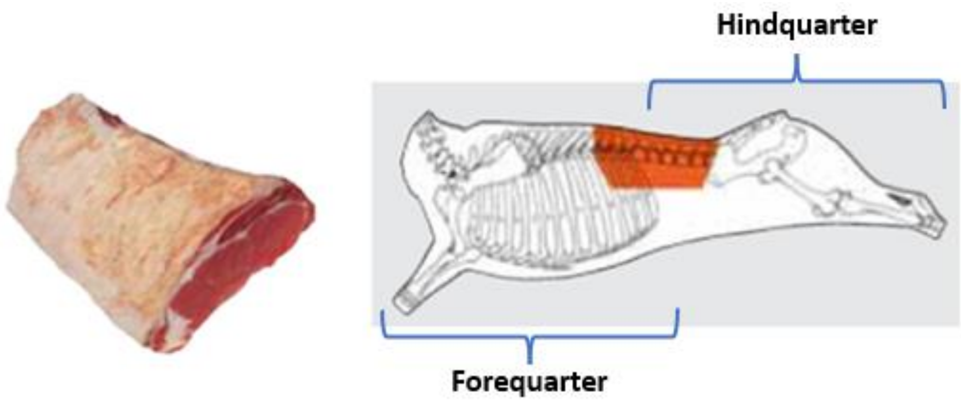


Figure 28: The location of the striploin primary cut in the cattle carcass (Standard, 2015)

Table 12: Typical measurements of a striploin cut (Khodabandehloo, 2018)

	Maximum	Minimum
Length	605 mm.	450 mm.
Width	245 mm.	200 mm.
Height	125 mm.	90 mm.
Weight	13 Kg.	5.4 Kg.

Two primary tissue components of striploin are: muscle and fat. The trimming operation occurs within the fat medium (subcutaneous fat) located peripheral to the muscle tissue. The primary substance of fat tissues is triglycerides consisting of glycerol and fatty acids. Firmness of the fat is influenced by the contents of fatty acids and the length of carbon chains (Schumacher et al., 2022; Wood et al., 2008). Subcutaneous fat is presented in a layered structure with air gaps randomly distributed (Khodabandehloo, 2018; Lonergan et al., 2019). Fat distribution is affected by age, breed, gender, environment and weight of the beast (Schumacher et al., 2022).

The thickness range of the fat layer is 5 to 60 mm (Border et al., 2019; Khodabandehloo, 2018). Striploin trimming operations remove excess fat and connective tissues from the beef striploin along the contour of the underlying muscle interface, leaving a residual layer of fat on top of the muscles. In the final form, the thickness of the residual fat and the overall shape of the trimmed cut is defined by market requirements. Excessive residual fat can lower the value of the product, whereas over-trimming can reduce yield and affect the taste of the meat when cooked (Khodabandehloo, 2018; Savell & Cross, 1988).

In the manual process of trimming, operators use sharp boning knives. The product is placed on a flat board with the fat side facing upwards (Figure 29). Operators begin from one side of the product and make progressive angled, shallow cuts (slicing) to remove the outer layer of fat, guided by the tissue interface between fat and muscle tissue. When trimmed, operators may portion it into smaller, market-ready products such as striploin steaks.

Skilled operators use a combination of visual and tactile perception to perform the trimming task. Visual perception is used to locate the cutting path, monitor the external state and behaviour of the workpiece, and determine the position of the cutting tool relative to the external features of the carcass. In contrast, tactile perception dominates where visual information is not possible. In temporal form, tactile sense enables discrimination on approaching tissues and tissue structures and to estimate the location of the cutting tool relative to the meat tissue interface even though the meat deforms in response. The operator makes informed judgments using this information, combined with knowledge and previous experience. Using tactile sense, the operator responds with strategy to achieve the required residual fat layer and the shape of the product by guiding the knife with anticipation of behaviour, the expected encounters with tissue features in the meat tissue and changes in response to the medium.

Figure 29: Manual trimming of striploin primary cut (Gordon Food Service, 2022)

1.2. Automation for striploin trimming

At present, no known commercially available robotic or other automation system is capable of performing the task of beef striploin trimming relative to the real-time position of tissue interfaces. Deformation in the meat during cutting operations requires real-time perception and corrective strategies to maintain cutting paths relative to meat tissue interfaces. Two important goals are to produce a product of conforming shape and tissue content, and to maximise yield.

Innovative approaches to automatically trim fat tissue from the striploin to form a consistent residual layer over the top of the product and to meet market requirements have been reviewed. Mechanical systems to push the workpiece against trimmers is one such example. This approach is without means to measure fat depth, which will vary accordingly to the distribution of stiffness of underlying tissues. Examples of such systems are described in patents submitted by Leblanc and Long et al. (Leblanc, 1992; Long & Thiede, 1995).

Other approaches revealed in details of patents generally follow the automation scheme of Figure 30 (Albert, 1980; Black & Lauritzen, 2015; Bolte & McKenna, 2012; Cate & McCloskey, 2000; Chenery, 1981; Johnson & Vandenbroek, 2005). This structure includes an upstream measurement unit, a processing unit, and a downstream trimming unit, all connected by means of transfer (rollers, pulleys and conveyors) to progress the product through the processing operation. Khodabandehloo et al. (Frontmatec, 2021) illustrated the significance of deformation induced errors using a commercial system for pork trimming. This method proved successful in pork trimming and not in red meat processing. Although there are structural similarities between beef, lamb and pork, the latter has more uniform fat distribution containing a greater concentration of unsaturated fatty acids, rendering tissues softer and more fluid such that peeling and trimming are readily achieved (Kauffman, 2001; Valsta et al., 2005; Wood et al., 2008).

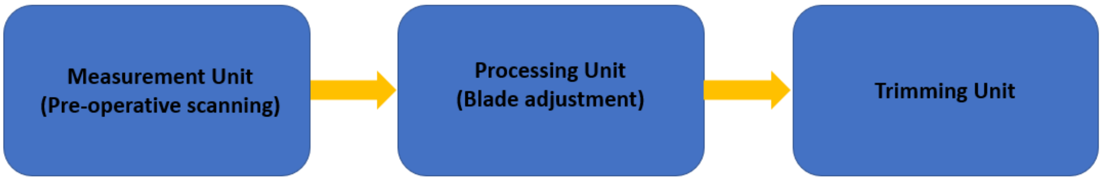


Figure 30: General structure for fat-trimming automatic units

The concept demonstrated in the above-mentioned systems relies on pre-operation data to perform the task of trimming and assumes negligible change in behaviour, position of tissues, and tissue interfaces during the operation. The approach also assumes near-uniform distribution of fat tissue across the workpiece.

Non-homogeneous shape is the norm across carcasses with significant variation in size. This combined with the deformable nature of meat tissues requires adaptive robotic systems to accommodate factors similar to manual skilled operators. Machine perception is a key function to discriminate between different hidden mediums when cutting and to follow a corrective cutting path by strategically adjusting the cutting trajectory in real-time.

Cutting meat tissues by machine to prescribed specifications will likely combine the merits of machine vision and tactile sensory capabilities. How to interpret tactile sensory data as real-time perception that will enable a robotic system to adapt in the automated task of cutting meat is the focus of this work. Tactile sensing provides an opportunity for perception to guide cutting in proximity to meat tissue interfaces where tissues and interfaces are hidden visually (Aly, Low, Long, Baillie, et al., 2023), however the means to retrieve appropriate information from tactile sensory data requires investigation. Previous attempts to use this sensory mode for following complex non-uniform cutting profiles, such as the aitch bone of the lamb hindquarter in (Steve Maunsell & Scott Technology LTD, 2018) and the femur bone of pork leg in (Guire et al., 2010), did not provide the anticipated yield.

The question to answer is not necessarily related to force values but rather the trends and character of persistent presentation in the form of sensory data transients. Here relevant information can be found to discriminate working conditions and the response of mediums during processing. This experience is typical when automatically sensing other natural mediums, such as on farms to detect weeds or pick fruits (Koirala et al., 2019; McCarthy et al., 2010) and within human tissue mediums in medical procedures to control micro-drilling and needle insertion-based procedures (Abolhassani, Patel, & Moallem, 2007; Brett et al., 1995; Brett et al., 2000; Peter N Brett et al., 1997; Peter N. Brett et al., 1997; Taylor, 2008).

In this paper, orthogonal (side of knife blade) reactive cutting force transients are explored in conjunction with force component transients of the leading tip of the knife to discriminate the orientation of the knife and its proximity to interfaces during the striploin steak trimming task. The work builds on a previous investigation (Aly, Low, Long, Brett, et al., 2023) where the effectiveness of reactive force transients on a knife to discriminate between tissues and the process of cutting meat tissue interfaces was demonstrated.

During the cutting process, the trajectory of the knife path needs to align with the interface between the fat layer and muscle tissue. The experiments described here characterise how force transients vary in response to a static knife approaching common features encountered within the meat. Additionally, the study proposes a cutting strategy to follow through with an automated process informed by the experimental results.

2. Methodology

Successful trimming of a striploin steak can be broken down into two steps. The first step involves recognising when the knife is approaching the interface between the fat layer and muscles tissue. The second step is to follow a cutting trajectory that encapsulates this interface at a relatively consistent distance from it. To achieve this, force transients from two different axes are considered. The force acting on the tip of the knife can be used to determine when the knife is approaching and penetrating an interface in the direction of cut, similar to the approach used in the experimental work of (Aly, Low, Long, Brett, et al., 2023). At the same time, orthogonal forces acting on the sides of the knife inform its direction to follow the path along the interface. Both these forces are crucial for discriminating irregularities or disturbances in the structure adjacent to the interface between the fat layer and the muscle.

For the purpose of exploring the influence of meat structure on the force transients, the trimming task has been simplified into shallow straight-line cuts. Each cutting path is progressively closer to the fat/lean interface in the striploin chop test samples. The advantage of using a straight-line simplification in the investigation is to enable observation and the identification of correlation between unique force transients and the path of the knife in the meat tissues.

2.1. Selection of sample for experimental investigation

Test samples were prepared using a whole striploin. This was sectioned into 40 mm thick portions to create striploin steaks. The choice of striploin steaks offers experimental advantages: (1)There is flexibility in the use of the same loin for different cutting investigations and for consistency in comparison; (2)The tissue structure of striploin chops closely resembles a two-dimensional model, and simplifies the process of correlating force sensor feedback with the position of tissue interfaces during deformation when using machine vision measurements and manual observation. Figure 31 illustrates a portion of a striploin steak derived from the primary cut.

Figure 31: Portioning striploin primary cut into striploin chops for experimental trials

2.2. Test rig structure

The experimental configuration was devised to represent conventional cutting procedures and used a 6-axis anthropomorphic ABB IRB 1200 manipulator. This manipulator was mounted on a support cabinet, and integrated with an adjustable table platform for accommodating meat samples. The rig is food-grade and IP67-rated. This ensures that all components are dustproof and waterproof, allowing for regular cleaning. Brackets were employed to secure the meat in place while enabling passage of the knife to cut through the fat layer (Figure 32).

Figure 32: The trimming bracket for holding the meat from the sides and enabling the knife to trim fat tissue

Experimental sessions were recorded using two Sony FDR-X3000 Action Cameras. The cameras were strategically positioned at varying angles to capture visuals of the knife position and motion response of the test sample. A knife blade with its grip removed was mounted on a customised bracket. The bracket, attached to a 6-axis ABB 165 force sensor, was attached to the manipulator final axis. The sensor is capable of 165 N maximum load in both the X and Y directions. The setup is shown in Figure 33. The recorded data from both the sensor and the camera enabled the extraction of force-time series data during the cutting process, which can be correlated with tissue characteristics and the cutting response.

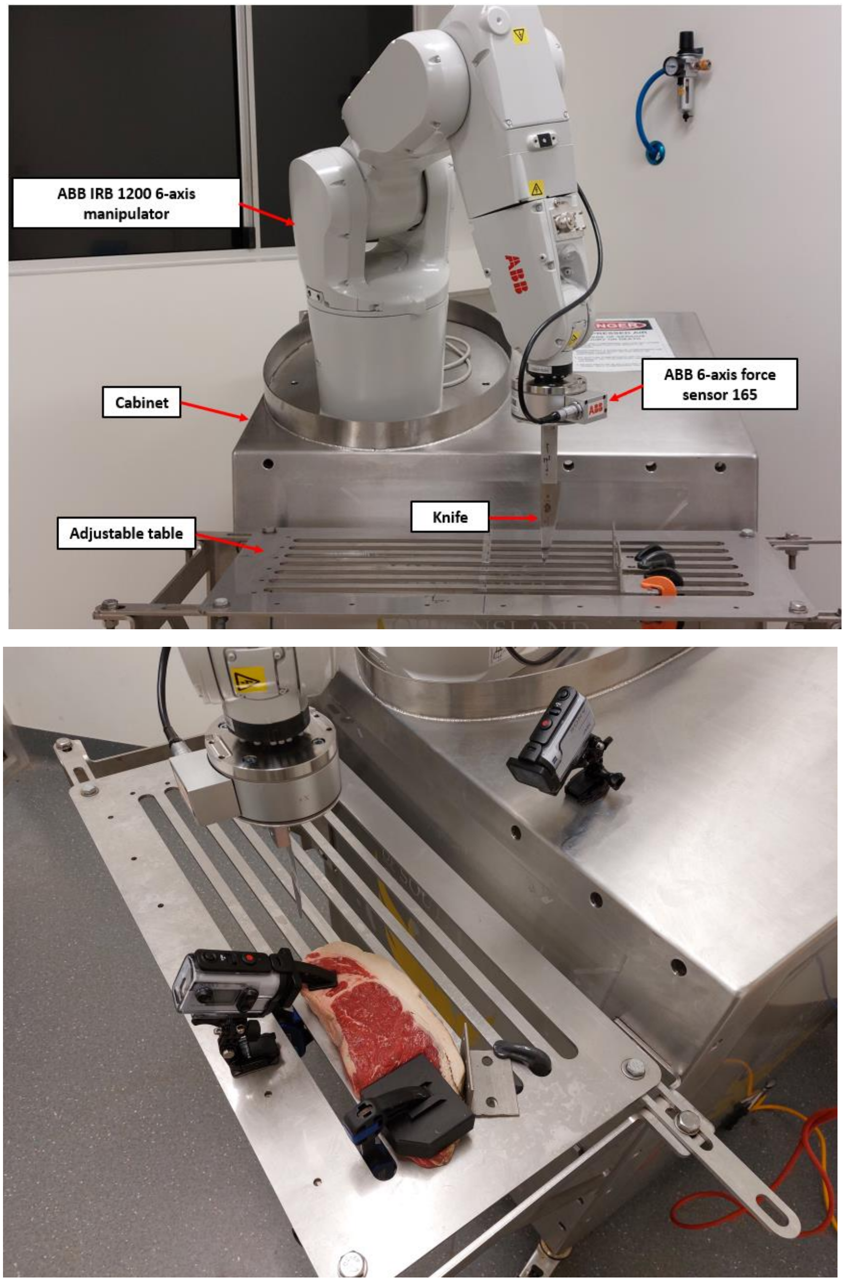


Figure 33: Test rig setup

2.3. Experimental preparation

Prior to conducting cutting experiments, the force sensor was calibrated to detect only the contact forces between the knife and meat specimen. The cuts were performed using ‘Points programming’, the cutting trajectory was determined and programmed 10 mm above the test sample (line 1 in Figure 34), and upon execution the manipulator lowered the knife by 30 mm such that cutting was achieved to a depth of 20 mm in the fat layer (line 2 Figure 34). Experiments have shown that the depth of the cut affects force values from the force sensor, but not the nature of the force transients resulting in discrimination of tissue interfaces. The velocity of the knife was set to be low, at 20 mm/second, and maintained at this constant rate throughout all experimental runs for consistency in controlled response to meat behaviour. Parameters such as the knife blade sharpness and surfaces were maintained after each series of cuts. The ambient temperature of the meat sample was maintained at a constant 9°C, similar to that of an abattoir. The blade cutting angle as applied to the meat was maintained on a perpendicular cutting plane aligned with the direction of motion of the knife.

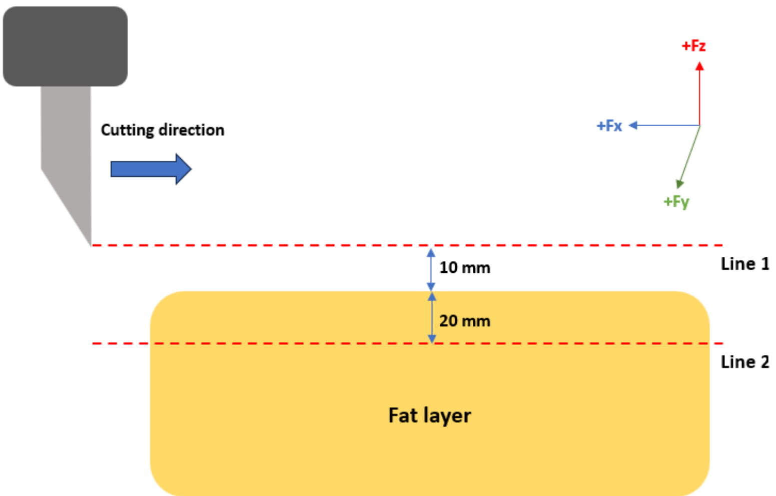


Figure 34: Programming the cutting line

An internal timer of the robot system was activated at the start of the cutting process. Following each experimental run, the robot saved data including the timer readings, and the corresponding force readings in .csv format. MATLAB was used for processing the data. The force sensor and video cameras were synchronised with the internal timer of the manipulator using a time stamp corresponding with the start of motion.

3. Results and observations

This section discusses the findings obtained from the experiments, including the observation and correlation of force transients with the location of cutting in meat tissues. This tactile interpretation identifies consistent trends and features in the force data that can be used by a machine to discriminate cutting events and update a cutting strategy in the meat. The forces instrumental to the discrimination of these events are illustrated in the schematic of Figure 35.

The effective force exerted at the knife tip in the cutting direction, the X-axis, is F_x and will be referred to as the compressive reactive force component ($F_{Compressive}$). This force comprises two components: one is required to initiate a crack and overcome the bonds between the tissues ($F_{Cutting}$), and the other responds to elastic tissue deformation ($F_{Deformation}$). There is a friction force component opposing F_x that acts in a shear direction across the surfaces of the knife blade. In the orthogonal direction of the Y-axis the force component is F_y and results from side pressure within the meat.

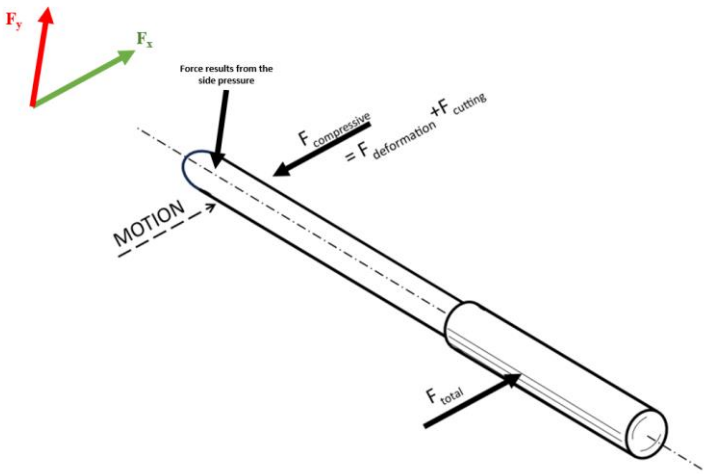


Figure 35: Concept schematic representation of the force components acting on the knife blade in the direction of cutting

In this particular cutting application, the approach needs to maintain an acceptable proximity of cutting trajectory within the fat and relative to the tissue interface. Notably, despite the heterogeneity found within red meat carcasses, consistent inherent traits of red meat exist and can be used to guide a cutting tool. A gap separating fat tissues envelopes the tissue interface, which is a common feature within the fat of a striploin. For this investigation, it serves as a natural pathway between the outer and inner fat layers and experimental studies have focused on discriminating entry into the feature and forces that guide following it on a cutting path.

Manual cutting observations have shown that this natural separation feature becomes more visible as the knife approaches it, offering a natural guide for trimming. The surrounding tissue exerts pressure and the surrounding tissues deform, funnelling the knife further into this natural gap. This phenomenon was reflected in the force transients as a recognisable pattern acting on the sides of the knife. Reactive force transients can be identified to discriminate following as opposed to entering or exiting this cavity. Primarily, lateral forces on the sides of the knife can be used to follow the space. Figure 36 illustrates some typical features of a striploin cut and shows the path between the fat layers. As depicted in the figure, the pathway encompasses the interface between the fat layer and the meat.

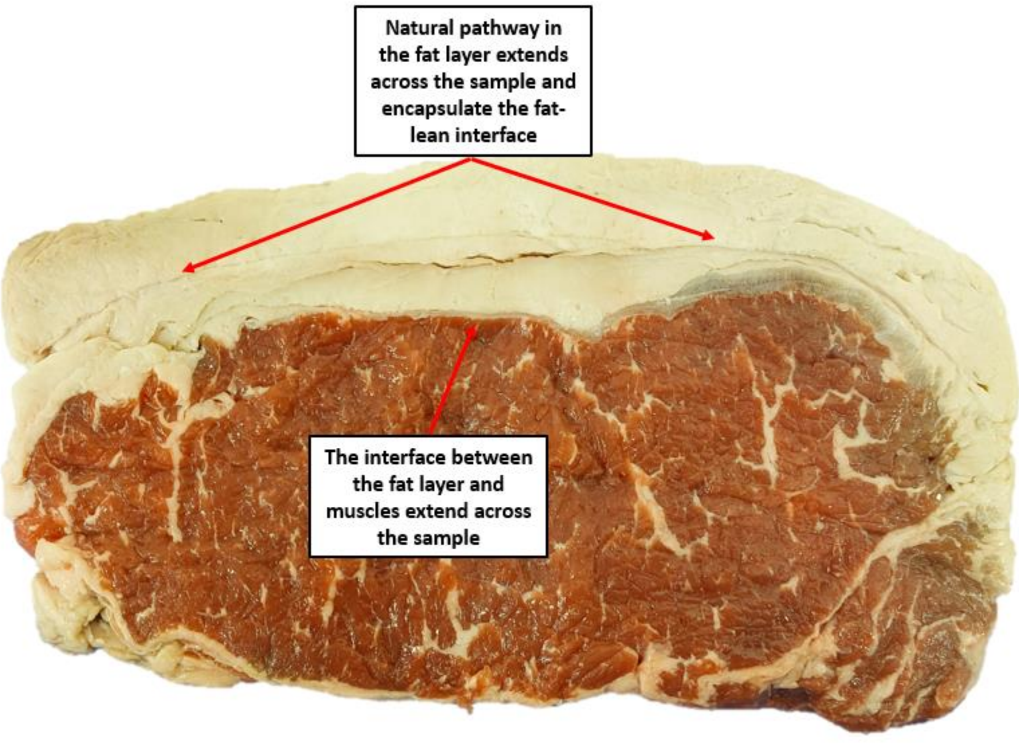


Figure 36: Features of fat layer

The investigation progressed in multiple stages, as outlined in this section:

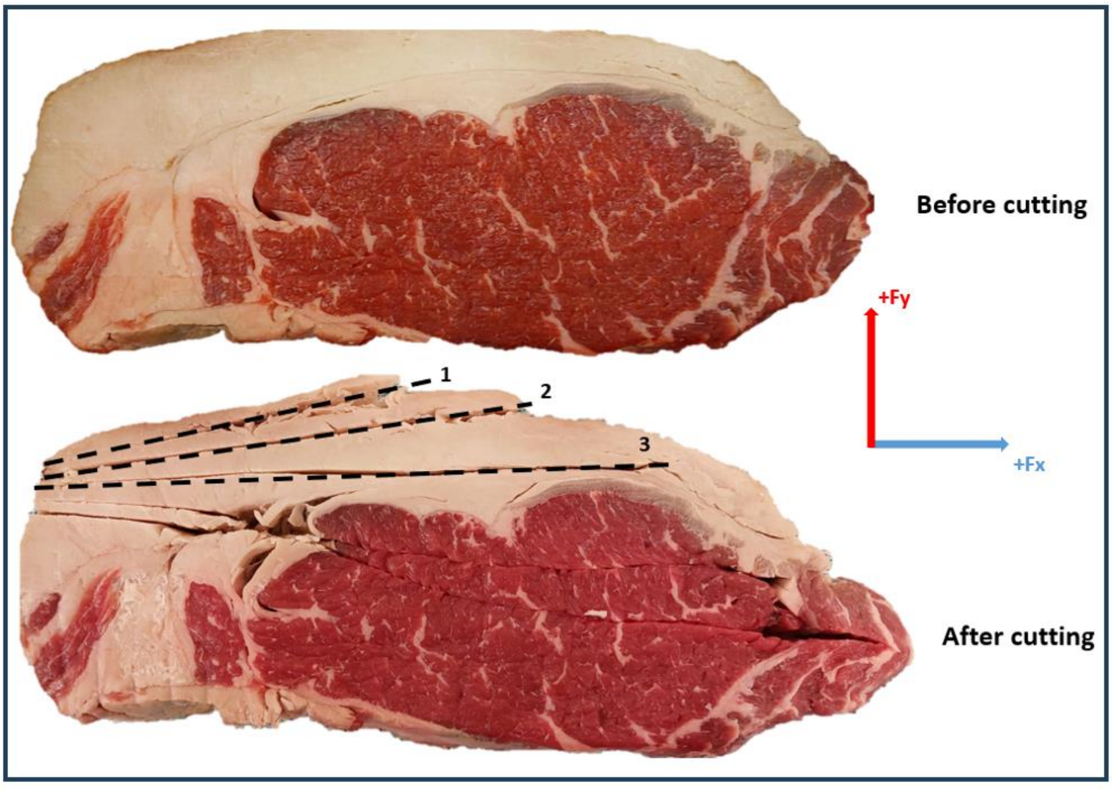
1. Investigate and identify changes in force transients when approaching tissue interfaces using visual and analytical observations.

2. Examine the unique force transients indicating that the knife is approaching and cutting through the pathway between the fat layers. Study how

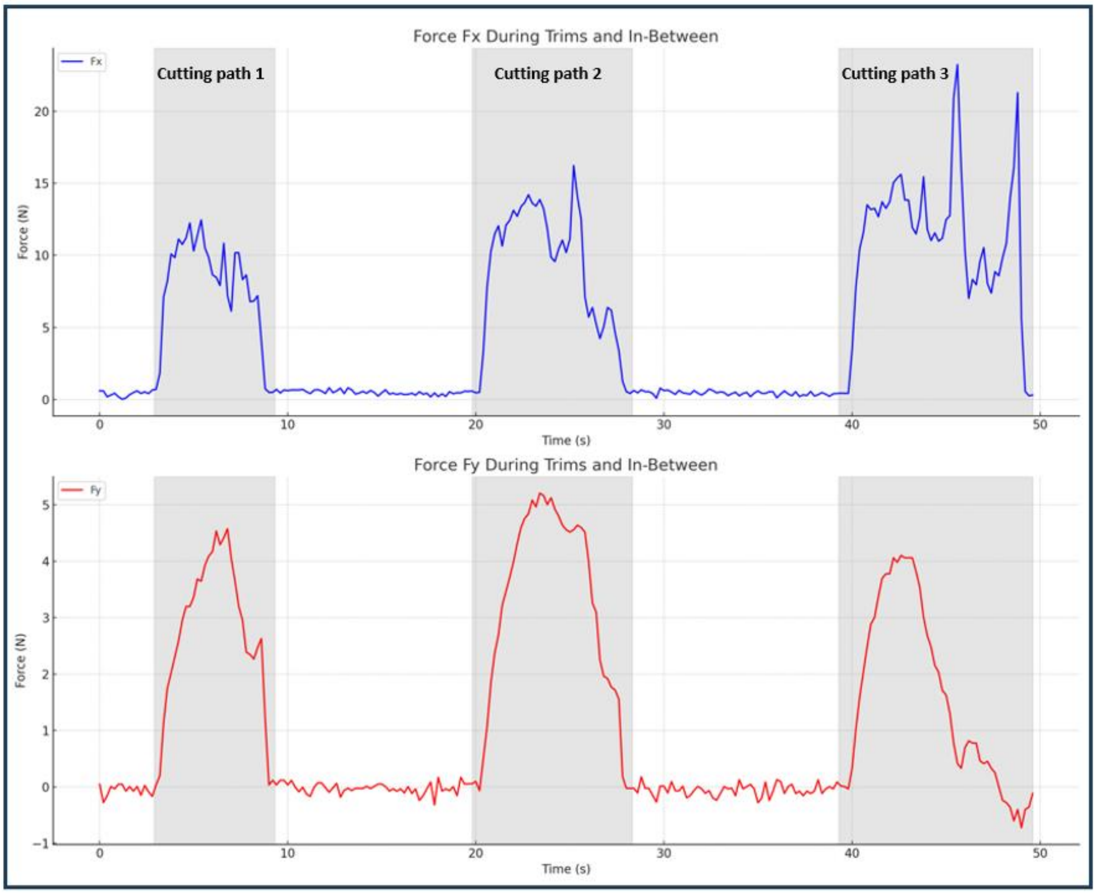
interactions between the knife and this pathway are reflected in the force transients.

3.1. Force transients on the approach to tissue interfaces

The first step is to identify the proximity of the knife to the fat/lean interface as it informs a decision of steering the knife towards or away if required. As the knife approaches the elastic sinew between the fat layer and the meat, the adjacent tissues begin to separate in anticipation of the blade. To investigate how force transients can be used to indicate the proximity of the knife from the fat/lean interface, three different cutting paths were performed in series with a rotation of five degrees between each cutting path towards the interface. Figure 37 shows the cutting paths with the corresponding measured reactive force transients on the tip of the knife F_x and the side F_y. Both visual inspection and statistical analyses were employed to contrast the transient force patterns as the knife moved closer to the interface on the sequence of paths 1-3. The experimental observations show that the workpiece geometry and some variations in material properties near the interface significantly influence the force distribution. This concept was empirically validated through a series of cuts that progressively approached the fat/meat interface.



(a)



(b)

Figure 37: Representation of cutting paths approaching the fat/meat interface

Visual observation of normalised cutting path data in Figure 38 shows that the forces on the tip of the knife fluctuate constantly due to the nature of fat as a material and randomly distributed air pockets within the fat layer. These forces only begin to increase abruptly as a result of local deformation when encountering and actively crossing an interface, as shown in cutting path 3. In contrast, the side forces are more stable and only begin to change when the knife encounters abnormalities on its sides.

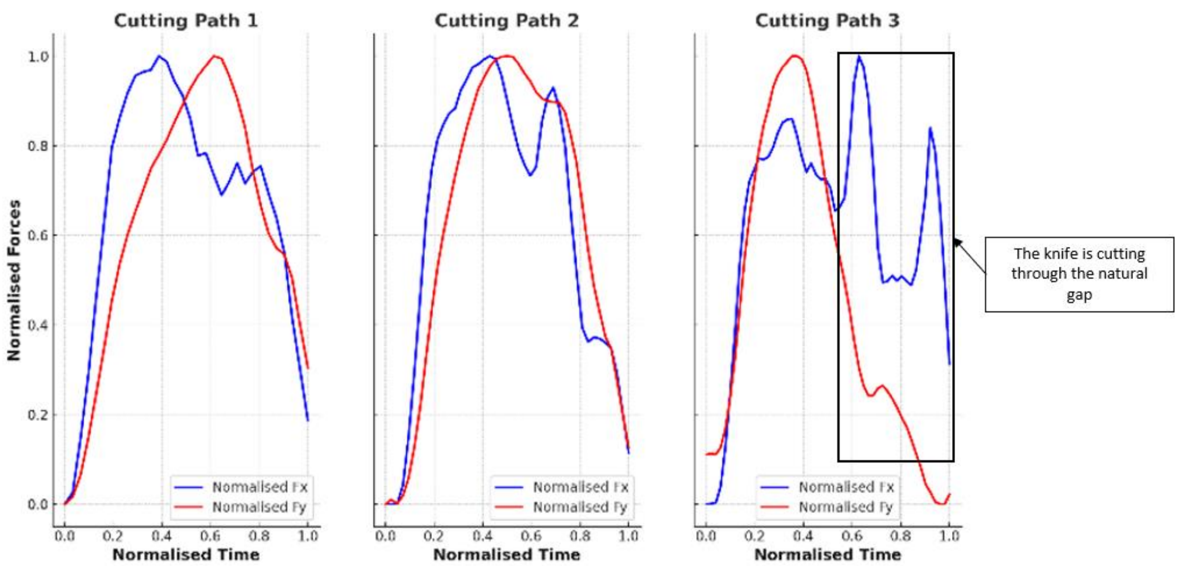


Figure 38: Normalised Fx and Fy on the knife for each cutting path

The visual observation of normalised cutting path data was confirmed by performing cross-correlation and data time warping (DTW) of F_x and F_y for each cutting path between the forces on the knife. The cross-correlation analysis and the DTW offer different aspects of comparing signals. Cross-correlation quantifies the degree to which two time series correspond to each other at different time lags (Yoo & Han, 2009). It is particularly useful for determining the level of similarity between two signals at the same time or with slight shifts. A high cross-correlation coefficient of normalised signals (close to 1) indicates linear similarities between the data, whether they are in-phase or out-of-phase. The signals are highly correlated if the cross-correlation plot has the highest peak at or near zero lag.

Alternatively, DTW is a technique that measures the similarity between two time series by optimally aligning them, even if they are out of sync (Müller, 2007). DTW allows for "warping" the time axes of the signals to make them more similar. The DTW score quantifies the "effort" needed to make the two signals identical. Unlike cross-correlation, which assumes a linear relationship between time series at various lags, DTW allows for non-linear warping of the time axis to align the series. Normalising the data prior to analysis focuses the comparison on the shape of the time series rather than their absolute values.

Table 13 shows the cross-correlation coefficient between F_x and F_y, and the DTW score for each cutting path. All three cutting paths showed positive correlations near zero lag in the cross-correlation analysis, with Paths 1 and 2 presenting very high coefficients of 0.95 and 0.97, respectively. This suggests an almost instantaneous and highly synchronised interaction between F_x and F_y, an observation substantiated by their low DTW distances (1.2 and 2.61). These low distances imply a strong similarity between the forces, suggesting a consistent and efficient cutting process.

On the other hand, Path 3 exhibited much lower cross-correlation coefficients (0.79) and elevated DTW distances (5.76). The path with fewer similarities and less closely matched forces in the DTW-aligned graphs reflects fluctuations in material properties supported by observations from the cutting videos near and at the interface.

Table 13: Cross-correlation coefficient and DTW score of cutting paths 1,2 and 3

	Cross-correlation coefficient	DTW Score
Cutting path 1	0.95	1.2
Cutting path 2	0.97	2.61
Cutting path 3	0.79	5.76

It is instrumental to focus discussion on cutting path 3, as it is the most close to the fat/meat interface from which to discriminate when the knife is approaching and penetrating the natural gap between the fat layers, and how this gap can be utilised to guide the knife relative to the interface.

Analysing the regions where F_x and F_y diverge can provide insights when the knife is approaching an interface. One simple approach is to compute the Pearson correlation coefficient between F_x and F_y over a predetermined window length of data throughout the time series. Although similar to normalised cross-correlation, Pearson correlation coefficients are calculated over a predetermined window length. The coefficient range is between 1 and -1 and is evaluated similarly to the cross-correlation coefficient. By selecting appropriate window lengths and step sizes, real-time calculation of the Pearson correlation coefficient is feasible. Setting a threshold for the linear similarity between the signals allows one to identify regions close to the interface.

In the analysis performed, the correlation between Fx and Fy was calculated over a window of 1 second to examine similarities between Fx and Fy for cutting path 3. In the figure, regions are highlighted green with strong correlation and red and orange with an opposite and weaker correlation. Figure 39 illustrates time periods when correlation is weak between Fx and Fy, indicating that the knife is approaching an interface and following the pathway between the fat layers. Table 14 shows the Pearson coefficient for each period.

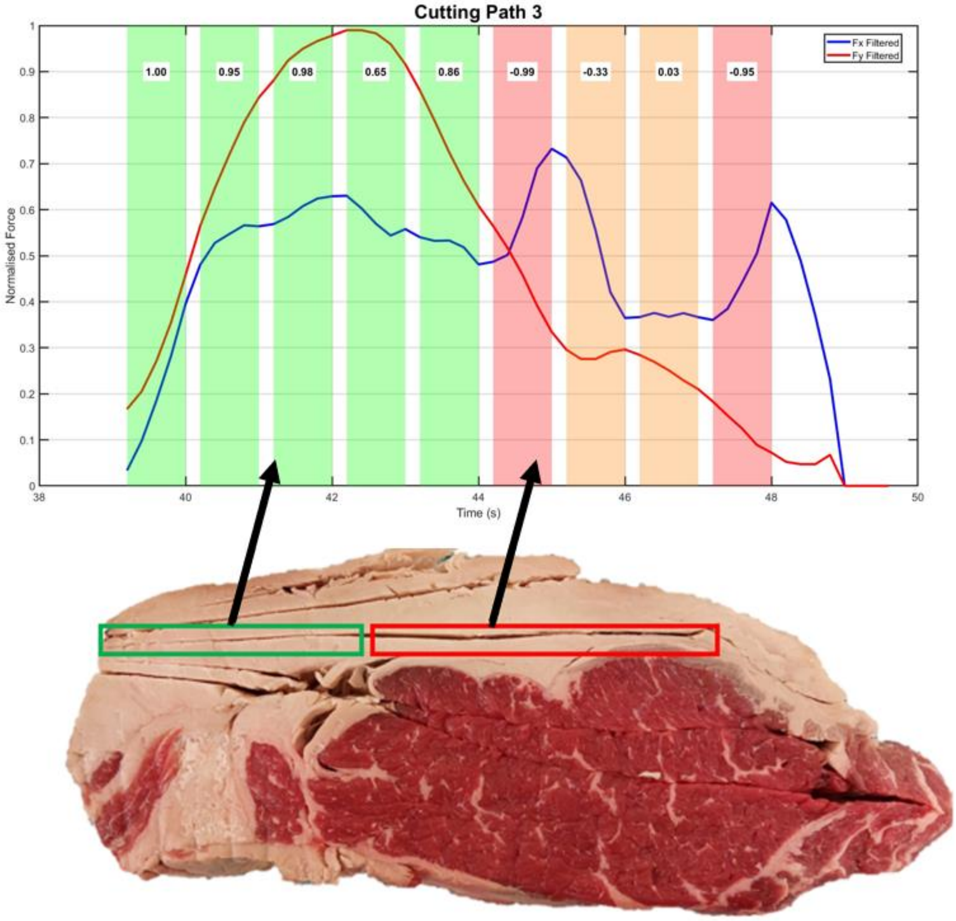


Figure 39: Visual representation of Pearson coefficient and the correlation between F_x and F_y for cutting path 3 (the data are filtered and normalised)

Table 14: Pearson coefficient for cutting path 3

Start time	End time	Pearson Coefficient	Correlation between F_x and F_y
39.2	40	0.997542	Strong
40.2	41	0.94705	
41.2	42	0.978612	
42.2	43	0.653762	
43.2	44	0.861972	
44.2	45	-0.98575	Weak
45.2	46	-0.33492	
46.2	47	0.034724	
47.2	48	-0.95013	

3.2. Interpretation of force transients

The force applied to the knife tip axis (F_x) was monitored by observing its rate of change (gradient). This approach was chosen based on previous observations (Aly, Low, Long, Brett, et al., 2023). The knife approaching or penetrating an interface is consistently marked by a spike in force gradient. The gradient of the force was computed from transients at 0.2 second intervals, a frequency sufficient to detecting significant force fluctuations and at a rate to reinforce persistent and reject anomalous readings when approaching an interface or when cutting through. Figure 40 indicates forces exerted on the knife tip (F_x) and their corresponding rate of change. In the rate of change graph, the focus is on two key features: the regions above the zero line, that indicate increasing force, and the points where the curve intersects the zero line, signifying regions where the force peaks before diminishing. Region 1 shows the first interface penetration at the start of the cut, region 2 shows the increase of deformation while the knife is approaching and entering the natural gap between the fat layer and region 3 shows the knife breaking through the last tissue interface, exiting the sample.

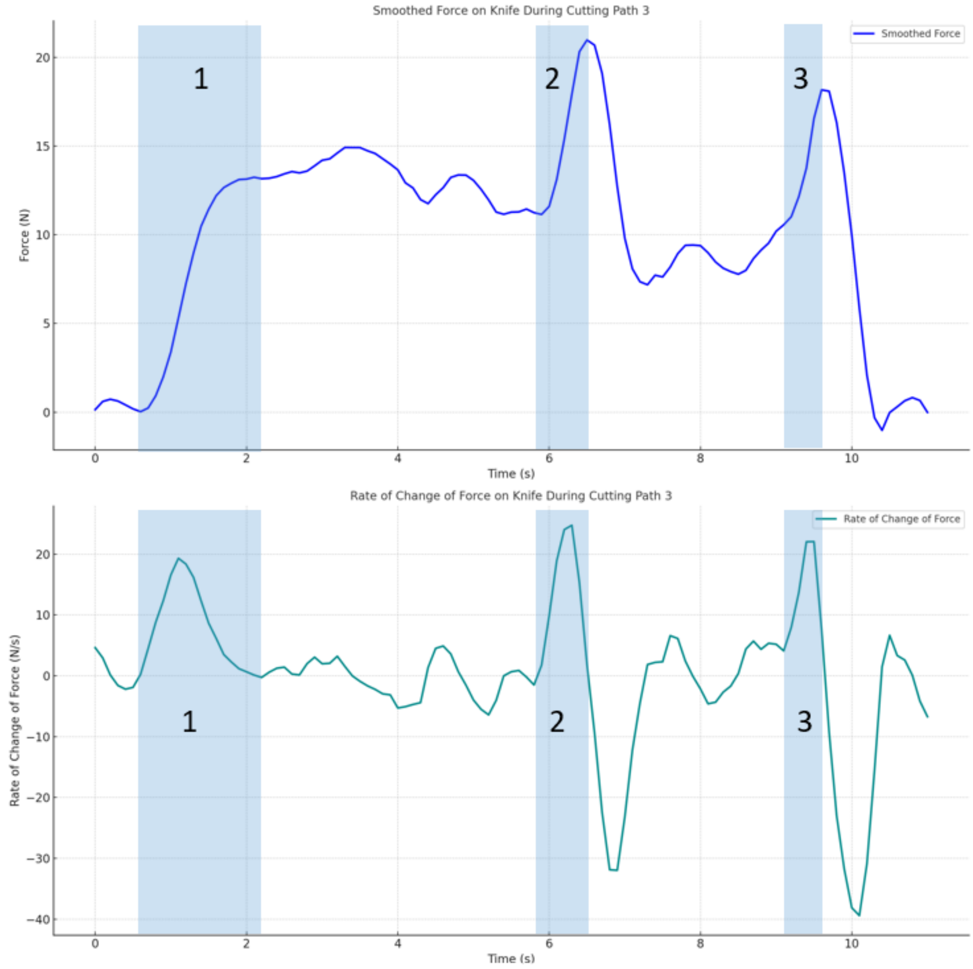


Figure 40: The force transient on the tip of the knife (Fx) and its rate of change

Figure 41 shows the correlation between the side forces F_y and the rate of change dF_y/dt with the features of the cutting path. Figure 41 (a) shows the predefined trajectory of cutting path 3 laid out on the actual cutting path, displaying how the pathway between the fat layers migrates from the straight-line trajectory. The blue lines represent time stamps at which the rate of change of F_y intersected with the zero line, representing local maxima or minima and shift of the side forces on the sides of the knife. The regions depicted with green arrows represent an increasing net force from the interface side and a positive rate of change, whereas the regions with red arrows represent the opposite.

At the start of the trimming trajectory immediately following penetration of the first interface, the rate of change force plotted as a function of time in Figure 41 (b) shows a positive trend. This indicates an increase in force exerted on the inner side of the knife from the interface direction of the sample (green area on the plots). Concurrently, an increase in the net force is observed, peaking at 39.37 seconds at the end of the first region. This phenomenon can be attributed to the positioning of the holding bracket. The fixed bracket serves as a focal point for maximal stress as it immobilises the sample. Subsequently, as the knife approaches and penetrates the natural separation between the fat layers, a comparison of the final cutting path to the predefined trajectory (indicated by the black dotted line) reveals the knife's tendency to deviate from the planned course as the tissues deform elastically against the knife and force alignment along the natural split within the fat layers.

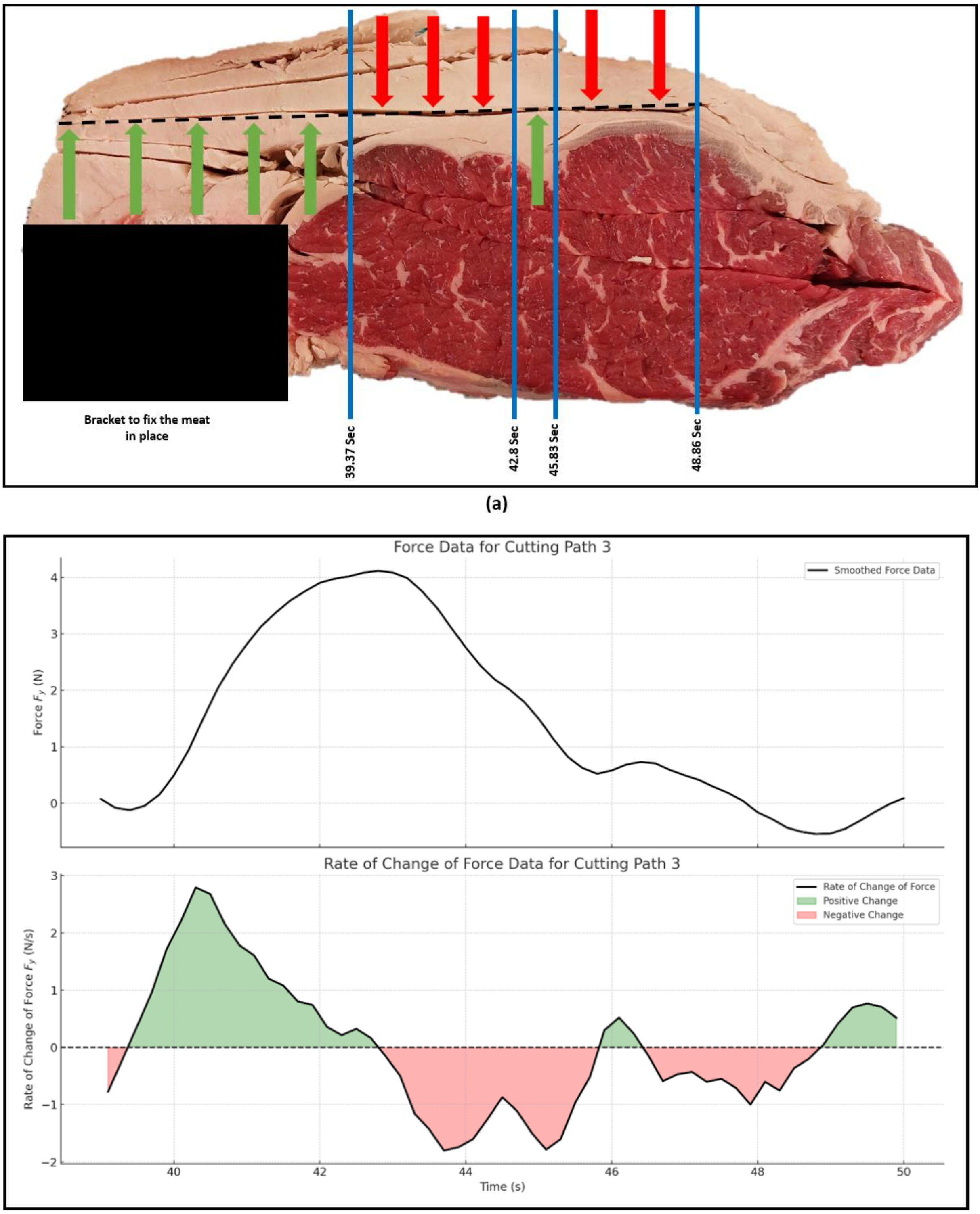


Figure 41: Side forces rate of changes during the trim

Another straight-line incision was performed on a different piece of meat, targeting a trajectory similar to cutting path 3 above. This incision, executed in close proximity to the fat/lean interface, also traversed the natural pathway between the fat layers. The purpose was to confirm the unique force transients observed in F_x shown in Figure 40 and to confirm the relationship between F_y and the structural characteristics of the cutting trajectory similar to Figure 41. Figure 42 shows the new incision, both the planned trajectory and the resulting cut.

Figure 42: The planned cutting trajectory and the result after performing the cut

Figure 43 displays similar patterns in force transients to those described earlier in Figure 40. The pattern similarity was confirmed using a further DTW analysis between the rate of change of F_x in Figure 40 and the rate of change of F_x in Figure 43. This yielded a similarity score of 1.41. Both graphs show unique transients represented by force peaks across three regions with smoother force transients in between. Region 1 depicts the initial interface penetration at the commencement of the cut, region 2 illustrates the increase in deformation as the knife approaches and enters the natural gap between the fat layers, and region 3 indicates the knife cutting through the final tissue interface before exiting the sample. At the same time, The side forces (F_y) and their rate of change in Figure 44 show a close correlation on how the natural path between the fat layer can guide the knife during the cut, similar to Figure 41.

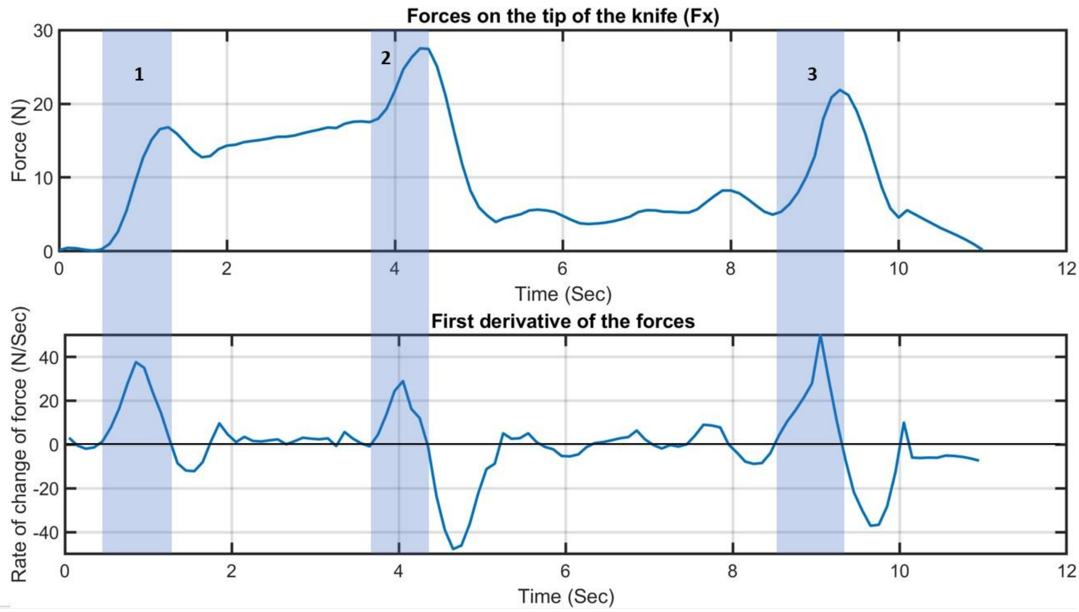


Figure 43: The force transient on the tip of the knife (Fx) and its rate of change

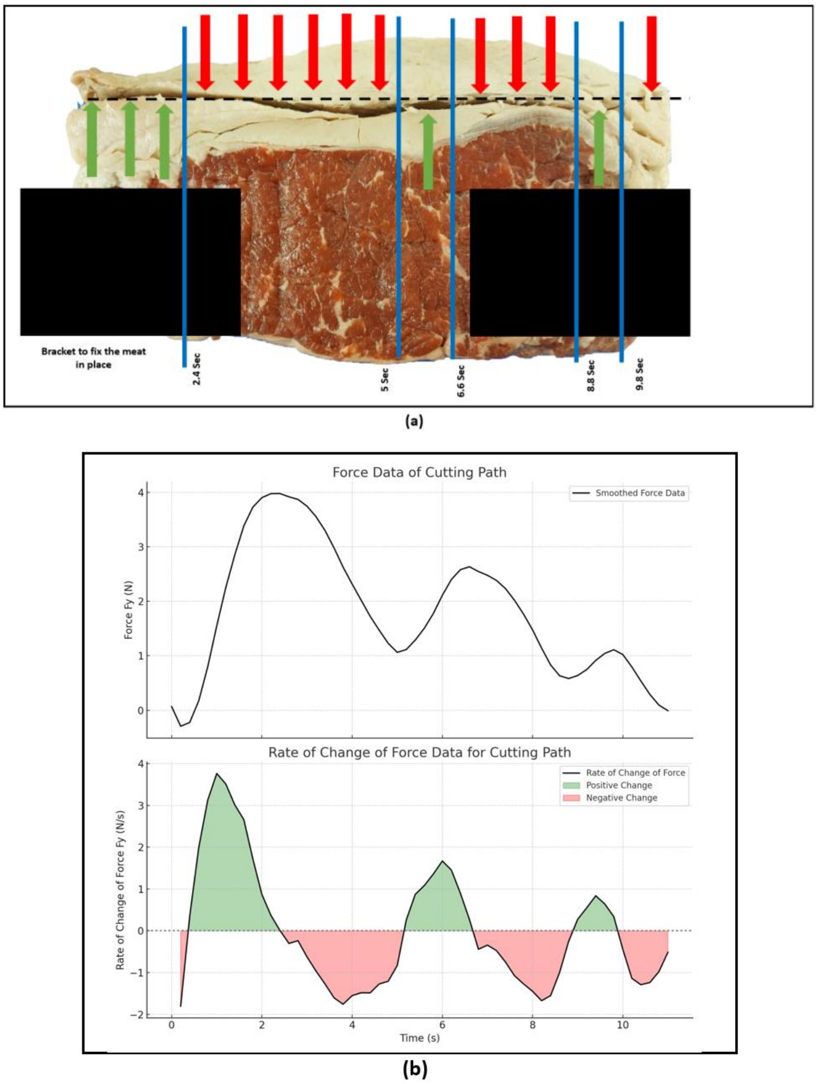


Figure 44: Side forces rate of changes during the trim

3.3. Formulation of a cutting strategy

The results have shown that the nature of force transients can be used to discriminate important conditions in cutting where decisions may be made to adjust guidance of the knife during cutting. The next step is to encapsulate this new knowledge into a strategy for machine guidance in the cutting operation. A cutting strategy based on the results and observations above can be summarised as follows:

1- Based on the external features and shape of the striploin steak, the knife is positioned to have a cutting trajectory aligned with the natural pathway between the fat layers in close proximity to the interface between the fat layer and muscles.

2- The knife makes initial contact with the carcass and starts the first tissue interface penetration in region 1 (as shown in Figure 40). In this region, the forces (F_x) increase and the tissues deform under the applied force until a mechanical limitation is reached.

3- Once the knife is fully inside the carcass, the force readings are maintained at a level to slice tissues. Sensor signals are monitored to discriminate the proximity of the knife to the fat/lean interface region.

4- The red region of Figure 39 and region 2 in Figure 40 show spikes in forces (F_x) in front of the knife due to deformation of the tissues as the knife approaches the natural pathway. This is on the approach to interface surrounding the cavity.

5- Upon entering the natural pathway, the knife follows the trajectory that offers the least resistance. The direction of the path trajectory is determined based on the directions of the force on the sides (F_y) by reorienting the knife based on the force signal shown in Figure 44.

6- The knife completes the cutting path by breaking through the last bit of tissue (region 3 in Figure 40).

The experimental evidence on force transients to discriminate the approach to tissue interfaces, discussed above in the paper, can be embodied in an automated sensory perception system that uses specified forms of tactile force transients to discriminate the important cutting conditions for the task at the knife blade. Following identification the strategy is to maintain the desired cut path with respect to the detected tissue conditions and either maintain the conditions or correct the cut path to avoid the incursion. This requires decision functions to select and control the path of the manipulator in near real-time. In the trimming operation for striploin steaks, the aim is to guide the knife and achieve a specified range of proximity relative to the fat/lean tissue interface. Using this approach will enable control of the knife to take recovery action in response to range of disturbances that are normally encountered within the tissue medium to maintain the planned cutting path.

In the task of trimming a striploin steak, a crucial decision involves identifying when the knife is approaching the fat/lean interface and entering the pathway between the fat layers. Then, react to the side forces to navigate the turning points accurately and follow the path of separation. This decision entails either rotating the knife to follow the shape of the path and react to the side forces presented in Figure 41 and Figure 44.

4. Conclusion

This paper introduces an approach to discriminate common tactile force features during a beef cutting operation that can be used to guide a knife attached to a robotic manipulator. The study focused on analysing tactile sensory data transients along two orthogonal axes on the knife, aiming to discriminate key interfaces during cutting. The two forces analysed are the side force transients and the orthogonal leading edge cutting force at the knife's tip. Coupling of the transients from these orthogonal force components showed a robust combination of signalling to discriminate the approach to tissue interface, which is a common feature to support machine perception when cutting meat.

Experimental confirmation of the correlation between events and the nature of force transients was used. The research derived the evidence by executing three straight-line cuts to represent the trimming of striploin steaks. Each path progressively approaches the primary interface between the fat layer and muscle tissue. Visual observations supported by cross-correlation and dynamic time warping analyses revealed stronger similarities in the orthogonal force transient components for paths farther from the interface, yielding 95% and 97% cross-correlation similarities and DTW scores of 1.2 and 2.6. However, as cutting approached the interface, the correlation weakened due to disturbances and tissue breakdown at this juncture. The cross-correlation in this case was 79% and the DTW score was 5.76. Pearson correlation analysis for the cut near the interface indicated that the decline in correlation began as the knife approached and sliced through the interface between fat layers near the main fat/lean interface.

For trimming striploin steaks, the interface between the fat layers serves as a pathway the knife can automatically follow, offering the least resistance and thus naturally guiding it in a manner similar to the technique used by skilled operators performing beef cuts by following such interfaces. The pressure exerted by the surrounding tissue channels the knife further into this natural gap. Moreover, lateral forces on the knife's sides demonstrated acute sensitivity to the contour of the natural path near the tissue interface, while forces aligned with the cutting direction indicated the knife's penetration into this path.

This paper demonstrates a novel approach to integrate tactile sensing for real-time machine perception during cutting that can be used in knife guidance by machine relative to tissue position. While the approach has proven robust and repeatable in identifying key features, further investigations are needed on a broader range of samples and applying these principles to different cuts.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Basem Ade Aly: Conceptualization, Investigation, writing- original draft.

Professor Peter Brett: Concept

Tobias Low: Writing- review & editing.

Derek Long: Writing- review & editing.

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DECLARATION OF COMPETING INTEREST

None.

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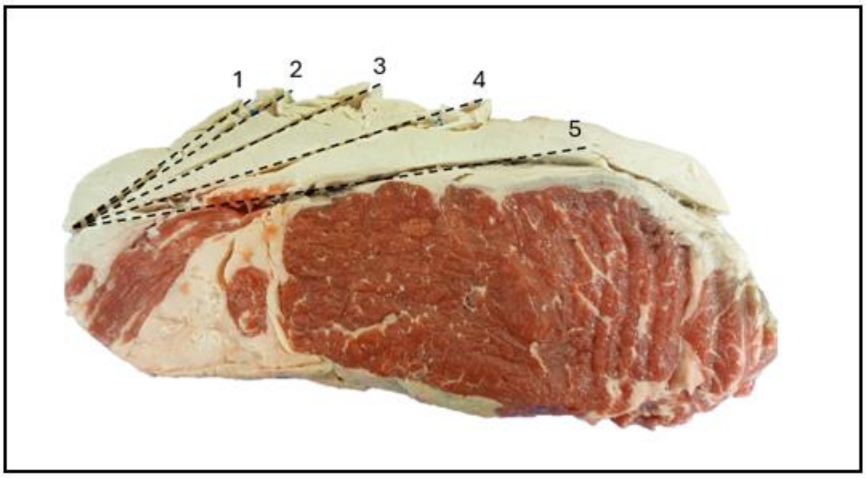
5.2. EXTENDED RESULTS

This Section presents the results of additional experimental runs conducted during the study of trimming fat from striploin steaks using robotic technology. The aim is to expand on Section 5.1 findings by analysing twelve cutting paths, key cutting events, and the unique force transients captured by the force sensor.

Section 5.1 detailed results from five experimental runs, which demonstrated clear correlations between the forces detected on the knife and the behaviour of the surrounding tissues. The study highlighted two main points. First, cross-correlation analysis can determine when the knife is approaching an interface. Second, interpreting the combined force transients from the knife's sides and tip can discriminate tissues and interfaces during cutting, as well as locate the knife relative to them.

The experiments in this chapter provide additional insights into the nuanced interactions between the cutting tool and the tissue under varying conditions. The experimental setup is the same as described in Section 5.1.

The section includes twelve experimental cutting runs, divided among four pieces of striploin steaks. The additional cutting runs are divided into 1) two sets of five cuts across the fat layer with varying insertion angles (see Figure 45 a) and 2) two individual cuts along a fat gap within the fat layer of the striploin (see Figure 45 b), totalling four new workpieces added to the experiment. The cutting paths and rotation angles were selected deliberately to cover a wide range of insertion angles, taking into account the thickness of the fat layer in the samples. Table 15 describes the samples.



(a)

(b)

Figure 45: a) Cutting paths with varying rotation angles as they near the fat/lean interface, b) An example to show cutting across the fat layer near or through an interface

Table 15: Description of the samples

Sample number	Number of cutting paths	Description
Striploin sample 1/2	5 Cuts	Each cut gets progressively closer to the lean/meat interface by rotating the knife
Striploin sample 3/4	1 Cut	A cut across the fat layer across interfaces.

The objectives of the analysis performed are as follows:

1. **Reflecting Key Events:** In all twelve cuts, test the capability and accuracy of the force transients in reflecting key cutting events, material features of the sample, and tissue behaviour around the knife.

2. **Approaching Interfaces:** In the ten cutting paths that progressively get closer to the interface in striploin samples 1 and 2, test the capability of cross-correlation analysis in revealing whether the knife is cutting away or approaching interfaces. As mentioned in Subsection 3.1, "Force Transients on the Approach to Tissue Interfaces," of Section 5.1, when the knife approaches the lean/meat interface, the perpendicular force components on the knife (F_x and F_y) become increasingly disturbed, reducing the cross-correlation coefficient between them.
3. **Exiting Fat Layer:** In cutting paths 1, 2, and 3 from striploin samples 1 and 2, which cut through the fat tissue away from the fat/lean interface, explore whether both F_x and F_y can indicate if the knife is nearing the edge of the fat layer, suggesting the need to rotate inward to prevent exiting.
4. **Following Interfaces:** In cutting paths 4 and 5 from both striploin samples 1 and 2, as well as the cutting paths from striploin samples 3 and 4, analyse the sensitivity of the lateral forces to the surrounding tissue behaviour and the contours of the encountered interfaces. This part should support the observations demonstrated in Subsection 3.2 "Interpretation of force transients" in Section 5.1.

5.2.1. Force transients on the approach to tissue interfaces

This section focuses on identifying the proximity of the cutting trajectory to the intermediate interface between the fat layer and the muscles. A cross-correlation analysis between the forces F_x and F_y was conducted on each cutting path of striploin samples 1 and 2. Table 16 presents the cross-correlation coefficients for cutting paths 1 to 5.

A high similarity between F_x and F_y indicates that the knife encounters no disruptions, such as interfaces or air pockets while cutting. For cutting paths 1 to 3, the cross-correlation coefficients show high similarity, confirming a smooth cutting trajectory. In contrast, for paths 4 and 5, the knife actively cuts through interfaces, resulting in significantly lower similarity between the forces. These results align with the findings in Subsection 3.1 of Section 5.1.

Table 16: Cross-correlation coefficients between F_x and F_y for cutting paths 1, 2, 3, 4, and 5 across test samples 1 and 2

	Striploin 1	Striploin 2
	Cross-correlation coefficient	
Cutting path 1	0.971881	0 0.986034
Cutting path 2	0.954827	0.981252
Cutting path 3	0.987867	0.970036
Cutting path 4	0.836709	0.875335
Cutting path 5	0.807018	0.761868

5.2.2. Cutting away from interfaces

This section examines cutting trajectories that diverge from the fat/lean interface, represented by cutting paths 1, 2, and 3, which exhibit high correlation coefficients between the force components on the knife (F_x and F_y). The stage of the cut of interest is when the knife is nearing the outer edge of the fat layer. This information helps in identifying the correct timing and location relative to the surrounding tissues, where the knife should execute the necessary rotation to trim or slice a uniform fat layer relative to the fat/lean interface.

The analysis of force data and tissue behaviour during cutting, in relation to the knife's position within the sample, reveals that the knife is nearing the outer edge of the fat layer when the force on the knife tip (F_x) starts to decrease gradually (indicated by a negative dF_x/dt) and the net lateral forces on the sides of the knife (F_y) reach their maximum on the inner side of the knife. These instances are depicted in Figure 46 for cutting paths 1, 2, and 3 of striploin 1, and in Figure 47 for cutting paths 1, 2, and 3 of striploin 2.

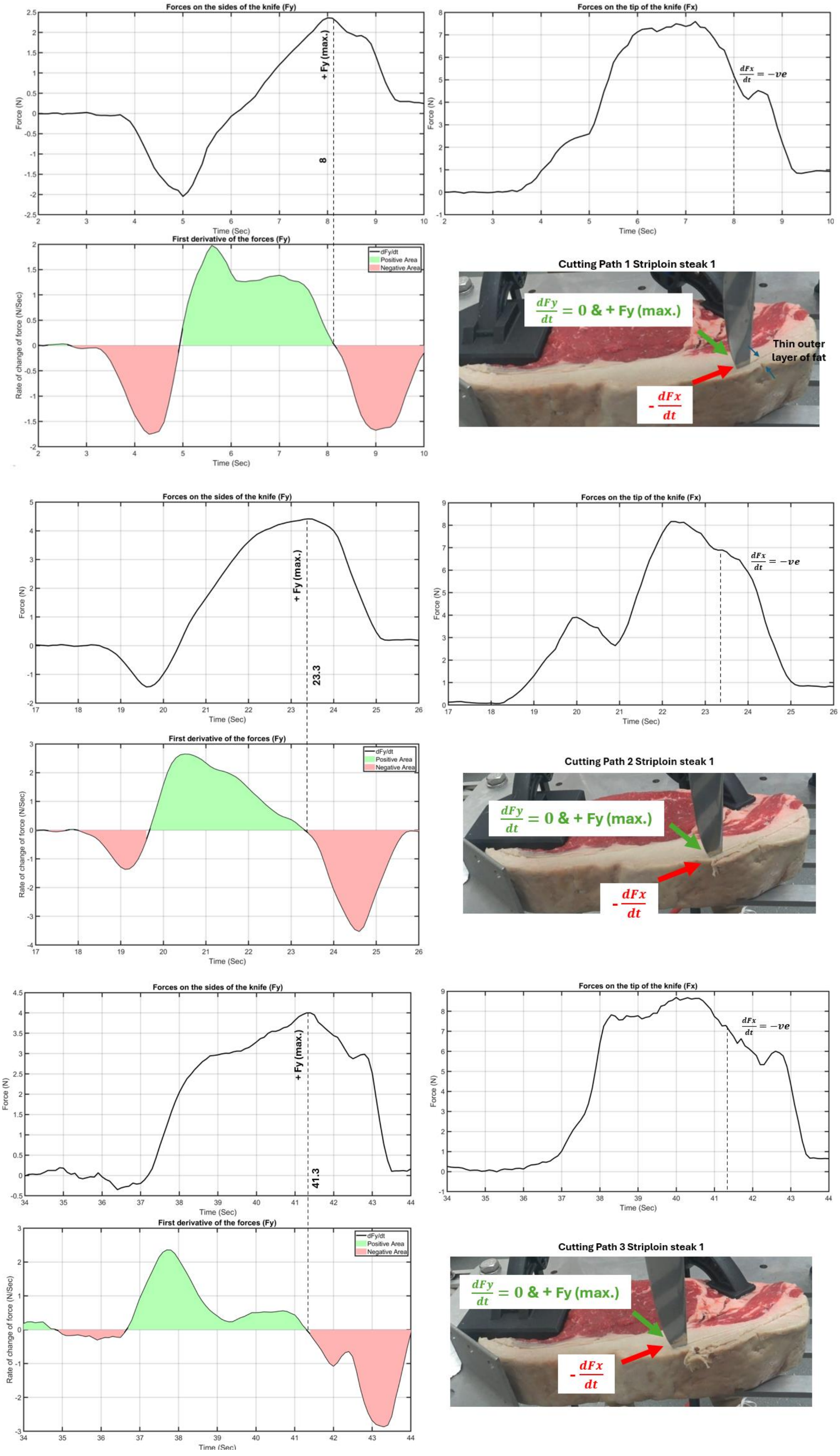


Figure 46: The time window that indicates the knife is approaching exiting the fat layer for cutting paths 1,2 and 3 of striploin 1

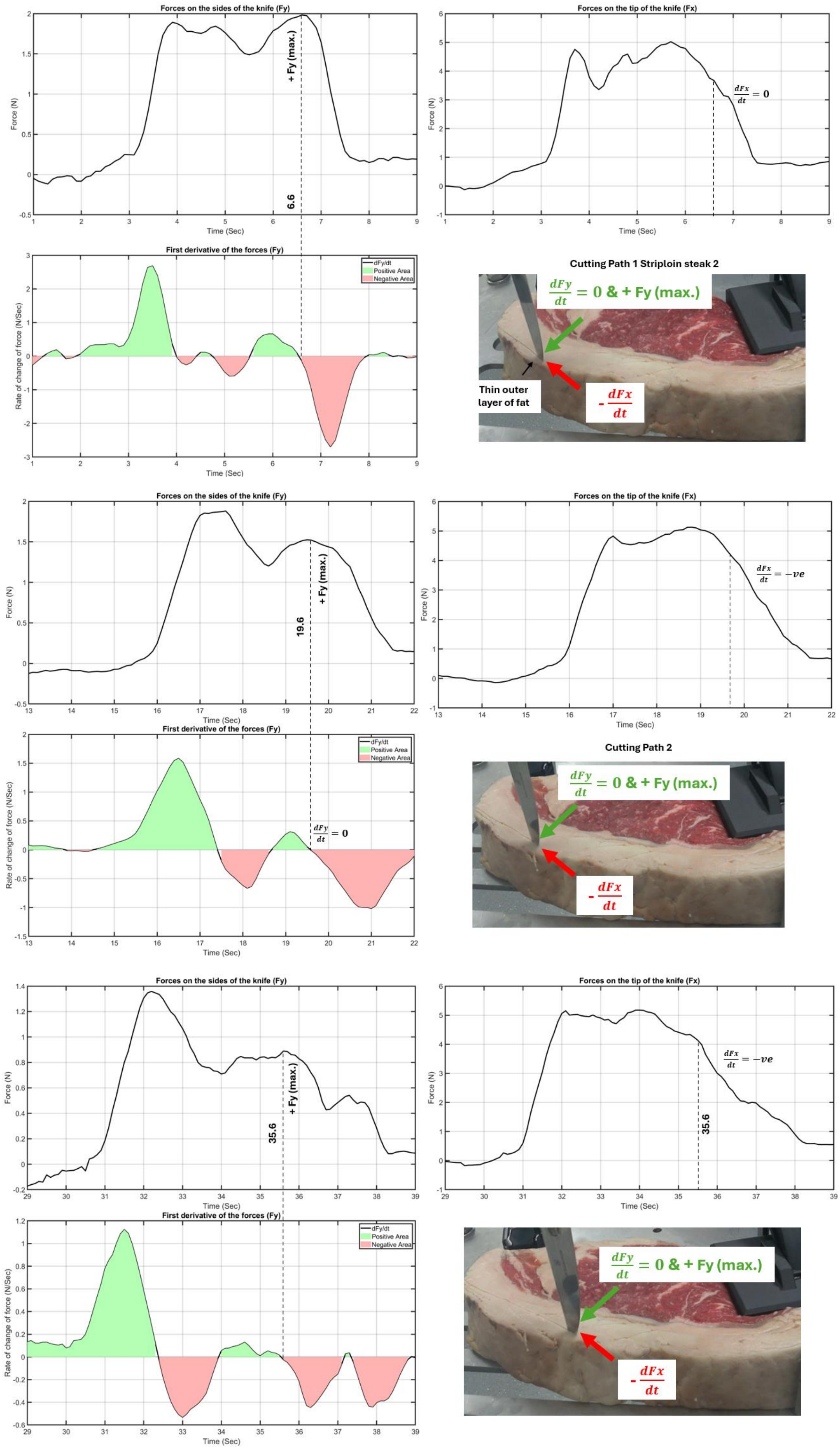


Figure 47: The time window that indicates the knife is approaching exiting the fat layer for cutting paths 1,2 and 3 of striploin 2

When slicing through a fat layer, the force on the tip of the knife increases upon penetrating the initial tissue interface until it reaches the necessary force required to slit the bonds between the fat tissues (Aly, Low, Long, Brett, et al., 2023). Subsequently, the force values stabilise as the knife progresses through the fat layer, depending on the length of the path. As the knife gets closer to the final tissue interface, the force on the tip of the knife (F_x) starts to gradually decrease (dF_x/dt is negative) as the knife gets closer to exiting the fat layer.

At the same time, the thickness of the tissue on the outer side of the knife diminishes causing the net lateral forces on the sides of the knife (F_y) to reach their maximum. The effective direction of the force component F_y is towards the inner side of the knife from the direction of the fat/lean tissue interface. The figures above illustrate the knife's location when these force conditions are met. It is noticeable that the knife is consistently positioned close to the outer edge of the fat layer, which is an ideal location for rotation if an automatic control strategy is implemented to guide the knife.

A MATLAB script was created to simulate the receipt of data in real-time and detect the cutting conditions mentioned above. The way the script works is that it loads the data from the Excel files and then processes each data point as if it were being received in real-time. A simple moving average noise filtering technique with a window size of 10 is applied to both F_x and F_y to smooth out short-term fluctuations and noise in the data. The derivative of F_x with respect to time is computed and also filtered from noise to identify the rate of change of force on the tip of the knife.

The script detects peaks in F_y data using the findpeaks function. It then iterates through the data points, updating a buffer that tracks the most recent data points. During each iteration, the script checks if dF_x/dt is negative and checks when a peak in F_y occurs during the period. When both conditions are met—dF_x/dt being negative for at least 0.5 seconds and a peak in F_y—the script records the time and relevant values of F_x, F_y and highlights them on a plot of Figure 48 and Figure 49. The table shows the times of the exiting conditions determined manually by correlating the force transients from the graphs with the cutting videos, and by using MATLAB. The MATLAB code is provided in Appendix B.

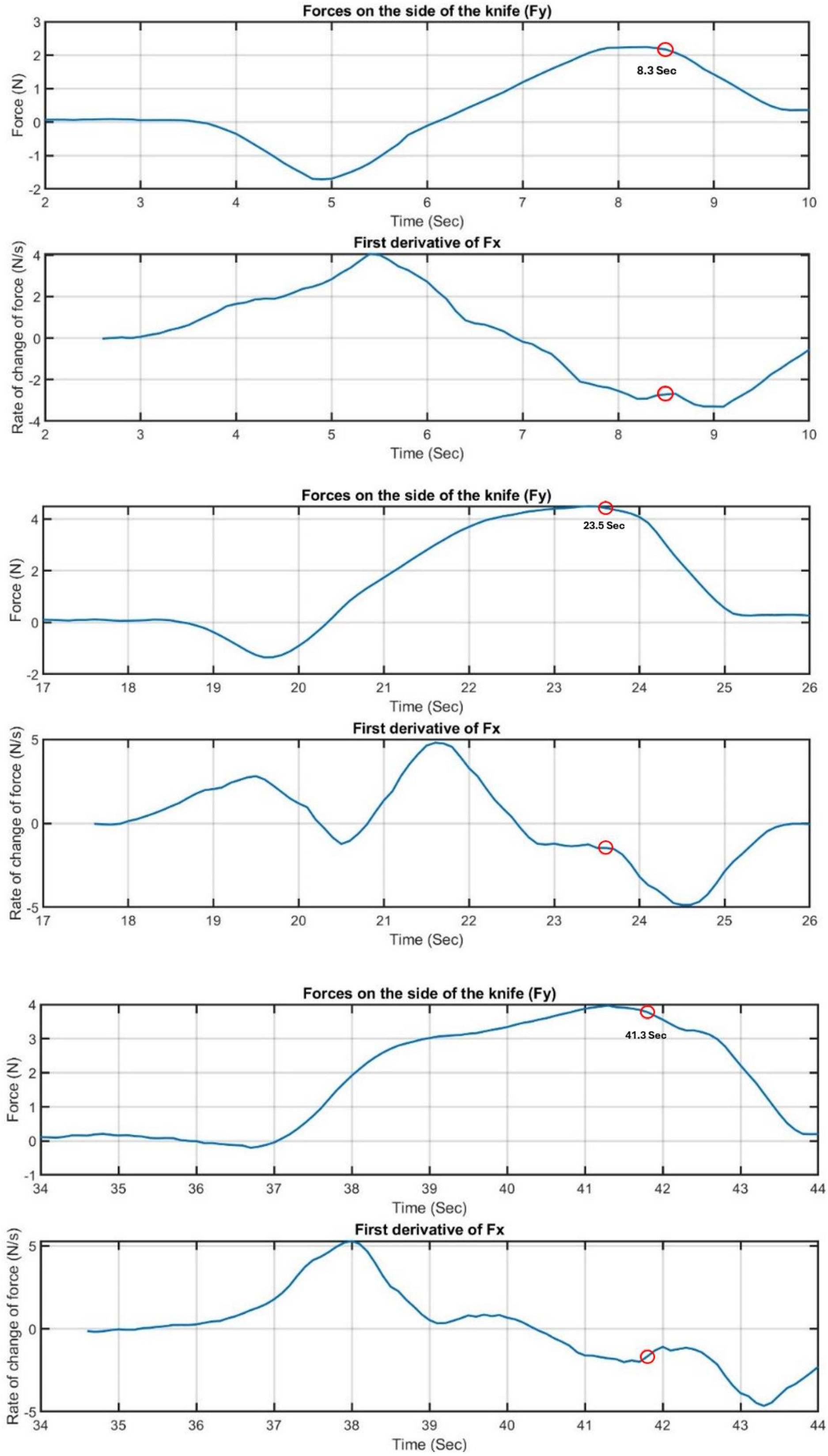


Figure 48: MATLAB simulation to detect the time window that indicates the knife is approaching exiting the fat layer for cutting paths 1,2 and 3 of striploin 1

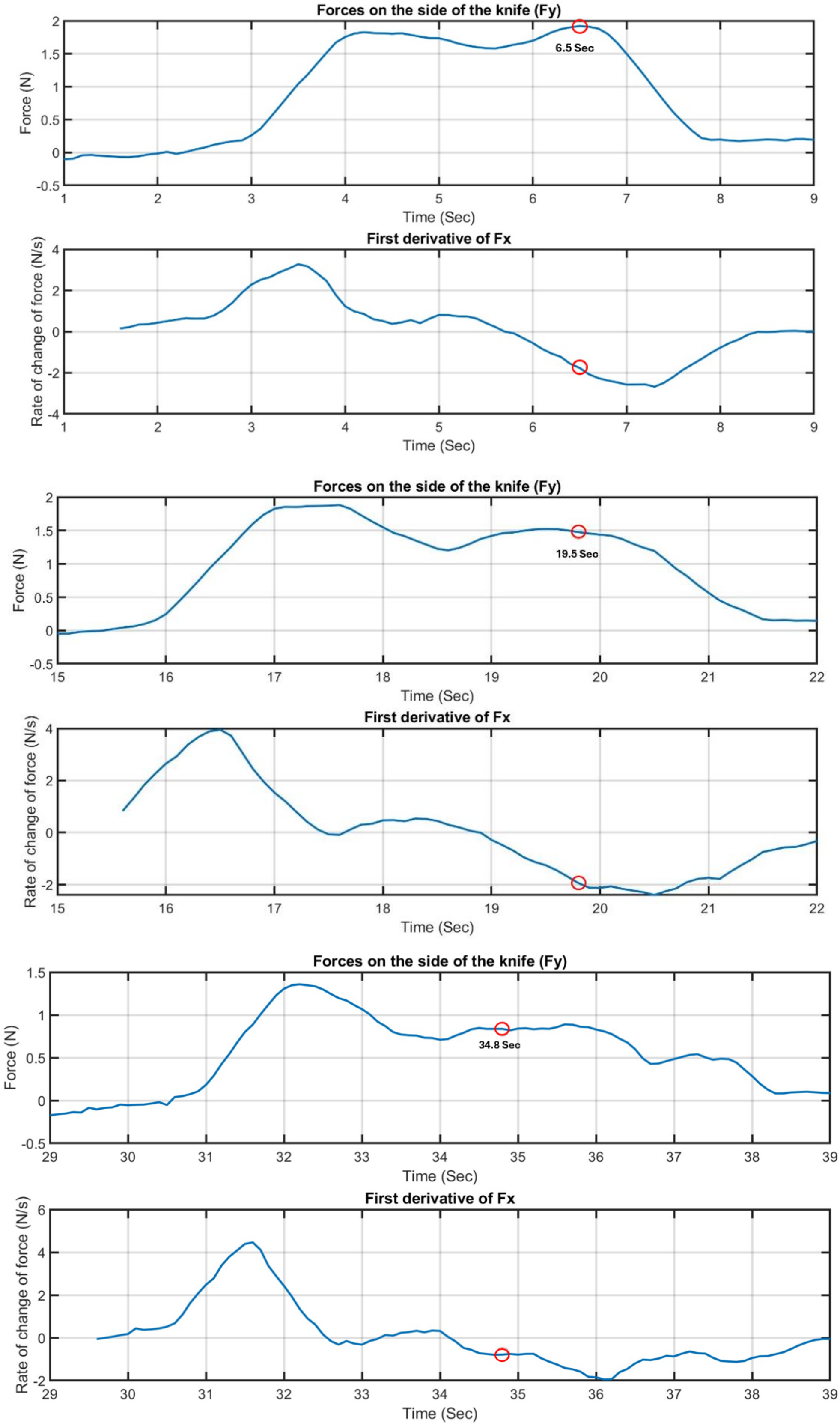


Figure 49:MATLAB simulation to detect the time window that indicates the knife is approaching exiting the fat layer for cutting paths 1,2 and 3 of striploin 2

Table 17: The time window of the knife close to exiting the fat layer detected manually and using MATLAB code

		Manual Method	MATLAB
Piece 1	Path 1	8	8.3
	Path 2	23.3	23.5
	Path 3	41.3	41.3
Piece 2	Path 1	6.6	6.5
	Path 2	19.6	19.5
	Path 3	35.6	34.8

5.2.3. Cutting through interfaces

The focus of this section is the cutting paths that encounter interfaces and natural air gaps in the cutting trajectory. The experimental trials detailed here aim to demonstrate the ability to identify instances where the knife cuts through interfaces or natural gaps and to show that the lateral forces observed reflect the behaviour of the surrounding tissues. Since cutting path 4 in striploin 2 only engages with a small part of the interface, the examples that will be presented are cutting paths 4 and 5 of striploins 1, cutting path 5 of striploin 2, and the cutting paths in striploins 3 and 4. The assessment of tissue behaviour in response to knife movement is derived from analysing cutting videos captured from various angles and correlating the timing from the videos with the force-time data provided by the force sensor integrated into the robot.

In cutting path 4 for striploin 1, Figure 50 illustrates the force transients on the tip of the knife (F_x) and the areas where the knife penetrates interfaces and moves between tissues. In the first region between 56 and 58.5 seconds, the tissue deforms while the knife penetrates a thin fat layer and the fat/lean interface, causing resistive force to accumulate before the penetration of the interface. Subsequently, there is a brief drop in forces between 58.5 and 59.7 seconds as the knife follows part of the interface within the cutting trajectory. F_x then increases as the knife returns to the fat layer until it begins to decrease steadily again as it approaches the final interface before exiting the fat layer.

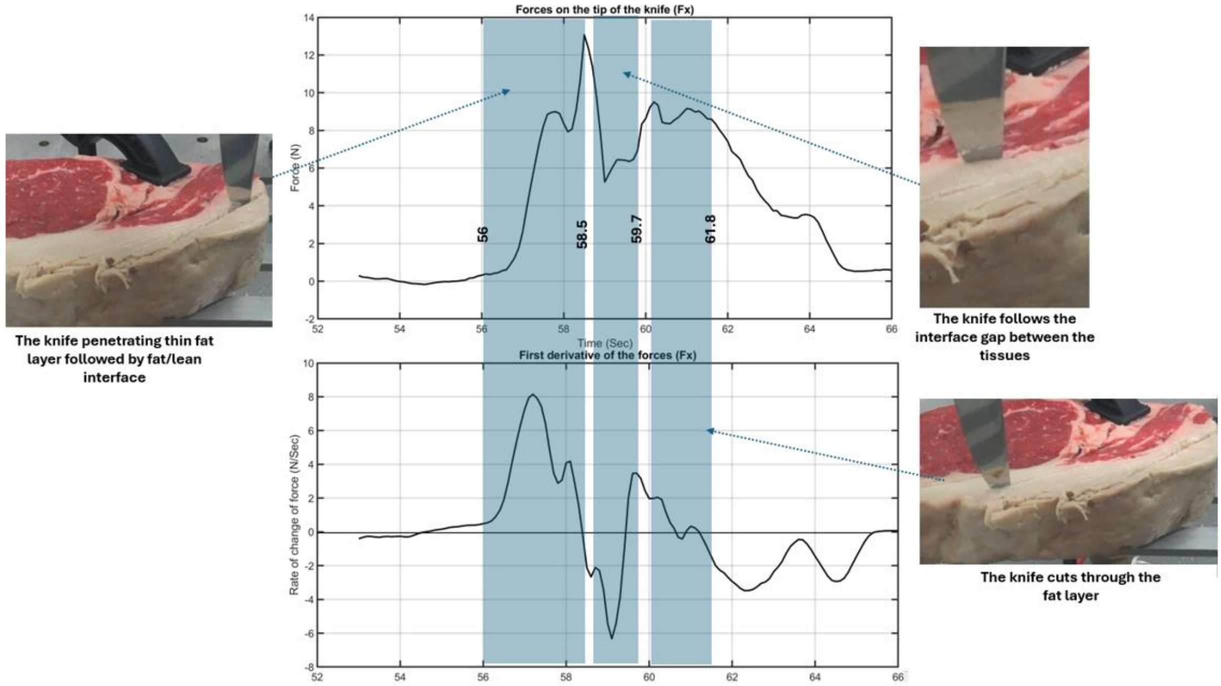


Figure 50: Force transients in the X-direction showing the instances of interface penetration for cutting path 4 in Striploin 1

On the other hand, the side forces (F_y) and their rate of change demonstrate the effect of the tissues on the sides of the knife. The behaviour of the force transients relative to the surrounding tissues showed similar patterns observed in Subsection 3 of Section 5.1. The direction of the changes in the lateral forces reflects the position of the fat/lean interface relative to the knife. Regions indicated by green arrows signify an increasing net force from the interface side, accompanied by a positive rate of change, whereas those marked with red arrows indicate the opposite.

Figure 51 displays the correlation between the lateral forces (F_y) and the rate of change (dF_y/dt) with features of the cutting path. It presents the predefined trajectory of cutting path 4 overlaid on the actual cut, demonstrating how the pathway among fat layers deviates from a straight-line trajectory due to tissue deformation.

At the onset of the trimming trajectory, following penetration of the first interface, the plot of the rate of change of force over time shows a positive trend. This signifies an increase in the force exerted on the inner side of the knife from the interface direction of the sample, as evidenced by the green region 1 on the plot between 56.2 and 58.1 seconds, where the net force on the knife's side reaches its peak. This can be attributed to the curved shape of the striploin steak and the positioning of the holding bracket, both acting as focal points for maximal stress as they immobilise the sample. Consequently, as the knife advances and penetrates the natural separation between the fat layer and the muscles, the rate of change of the lateral forces becomes negative. This occurs because, as the knife follows the fat/lean interface, the more malleable muscles end up on one side of the knife, while the stiffer fat layer is on the other side, causing a shift in the lateral forces.

As the knife re-enters the fat layer (green region 3 and red region 4), the pattern of lateral forces and their rate of change closely resembles that observed for cutting paths 1, 2, and 3. The force exerted on the inner side of the knife from the direction of the fat/lean interface increases until it nears the exit of the fat layer, where it begins to gradually decrease again (at 62.7 seconds).

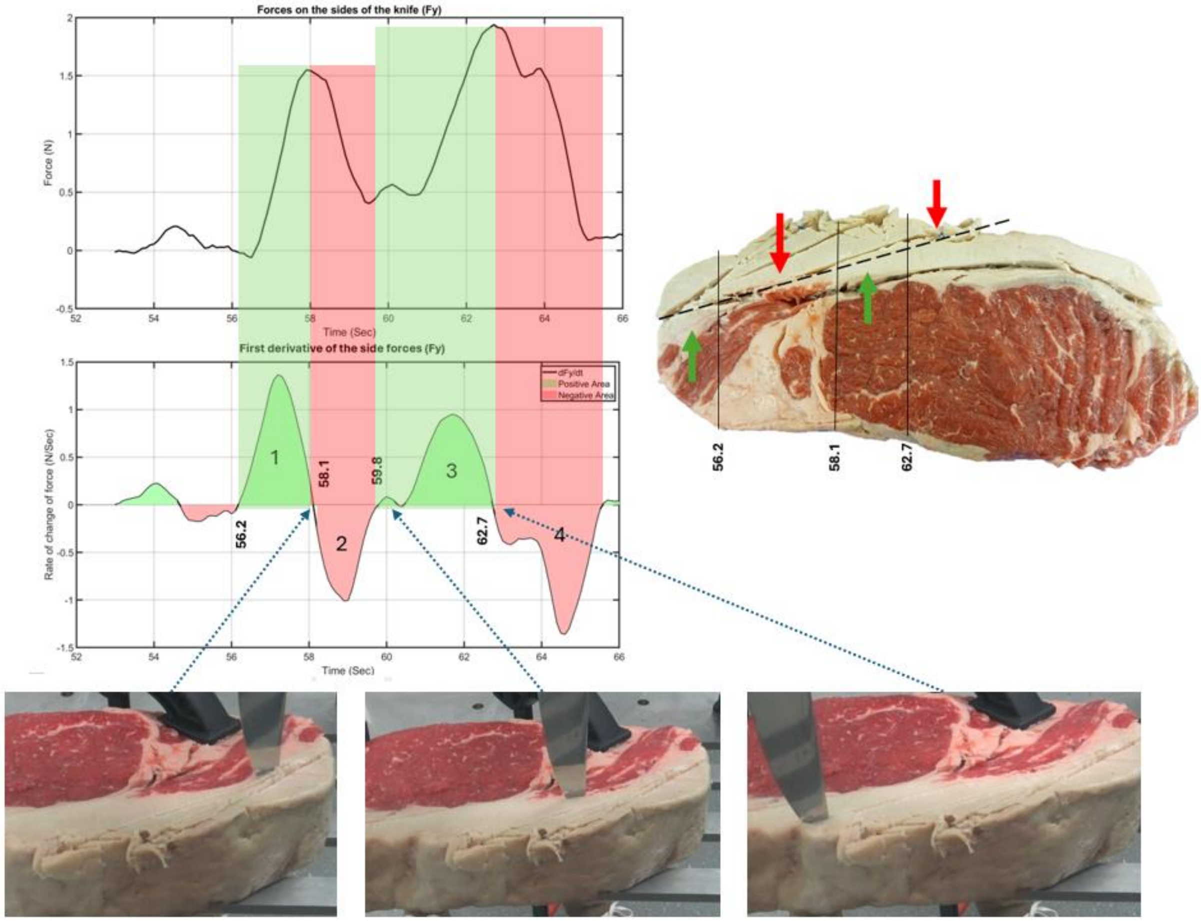
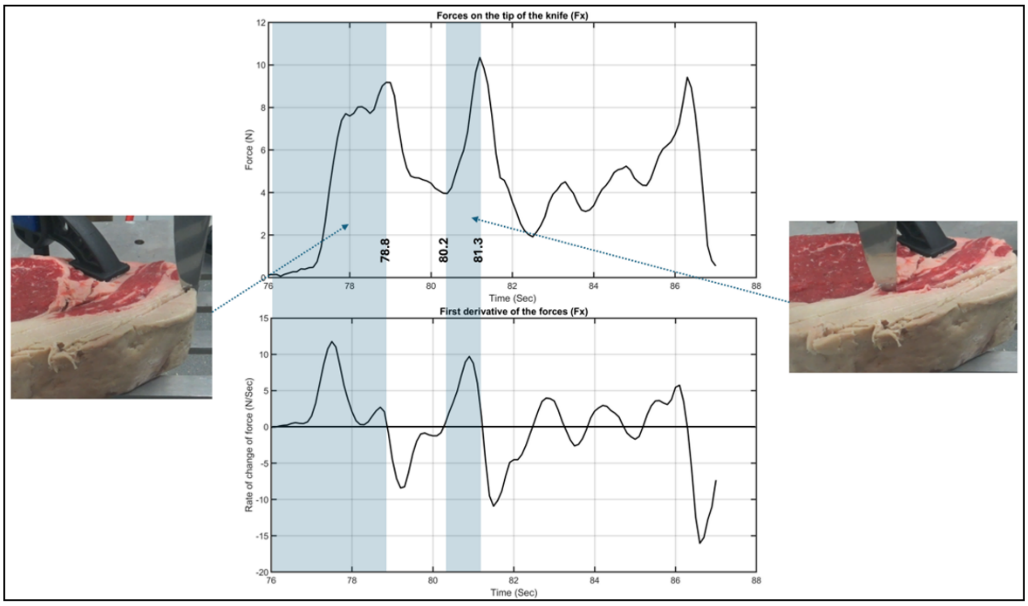


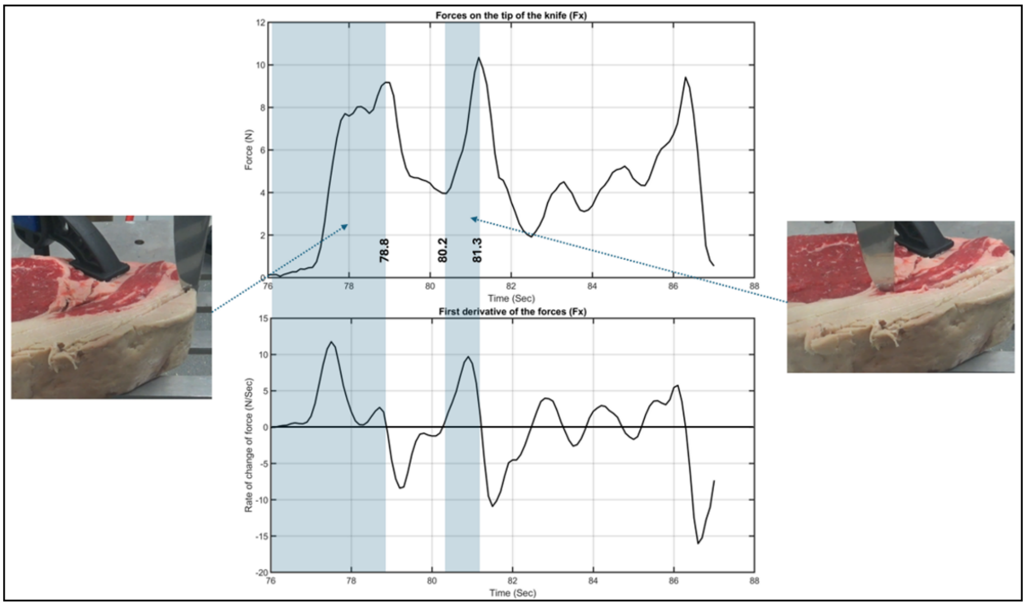
Figure 51: Force transients in the Y-direction showing the effect of the tissue behaviour and distribution on the lateral forces for cutting path 4 of striploin 1

In cutting path 5 of striploin 1, we observe a notable encounter unique to this path, a piece of fat located across the striploin. The penetration of this area is reflected in the spike of F_x due to tissue deformation at 80.2 seconds (Figure 52 (a)).

For cutting path 5 of striploin 2, the first highlighted region that ends at time 74.3 shows the penetration of both the first interface followed by the fat/lean interface due to the short cutting distance between them (Figure 52 (b)). The lateral force profile of cutting paths 5 of striploins 1 and 2 is shown in Figure 53.

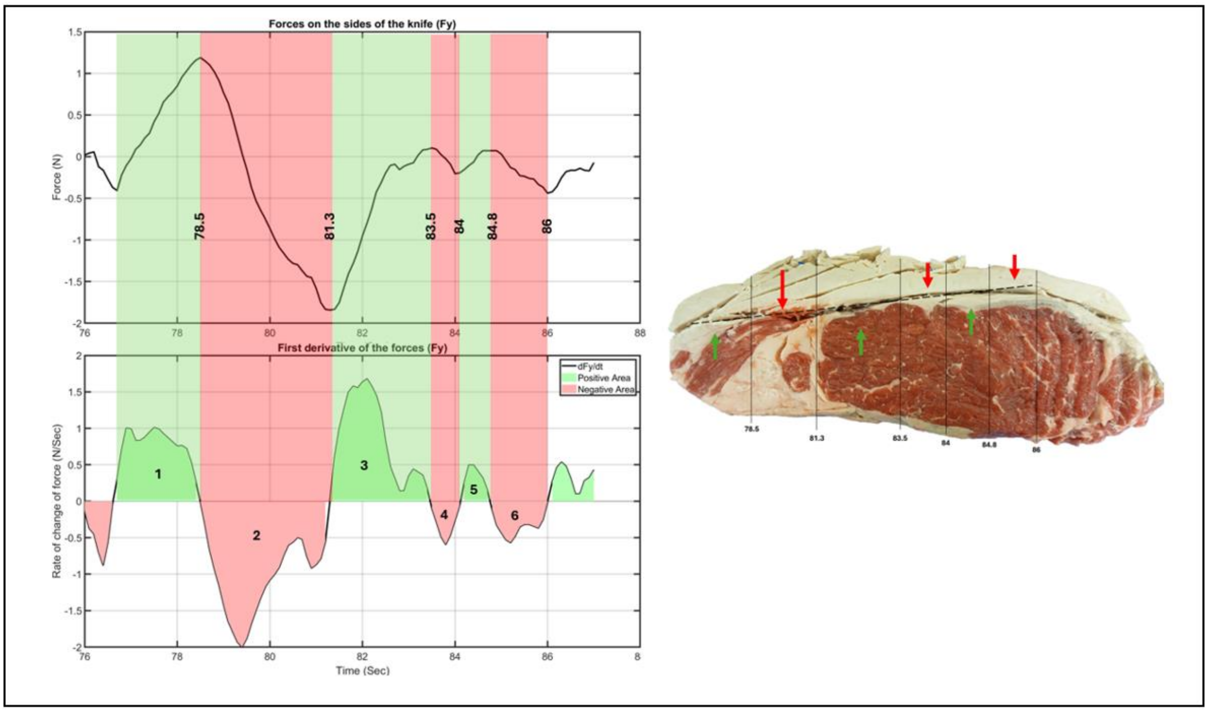


(a)

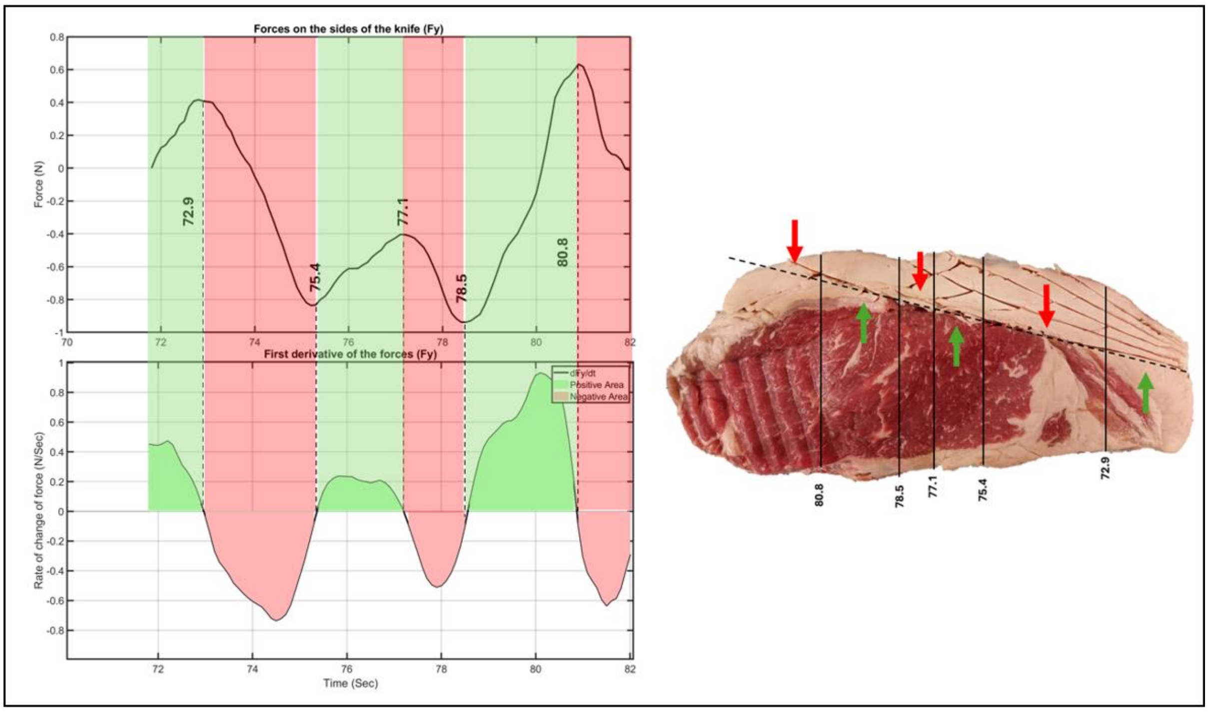


(b)

Figure 52: Force transients in the X-direction showing the instances of interface penetration for cutting path 5 of striploins 1 and 2



(a)



(b)

Figure 53: Force transients in the Y-direction showing the effect of the tissue behaviour and distribution on the lateral forces for cutting path 5 in Striploins 1 and 2

The experimental trial performed on Striploin 3 had a similar issue as the cutting of Striploin 1, a slight misalignment between the knife and the test sample caused the experiment to commence from a position different from the intended one. Moreover, excessive tissue deformation resulted in the knife not only trimming the fat but also cutting through the muscles. However, the results still revealed a robust and precise correlation between the forces applied to the knife and the tissue behaviour.

Two instances of deformation were observed and demonstrated in Figure 54: the first instance, occurring approximately between 2 seconds and 4.6 seconds, depicts the knife penetrating interface number 1 from the fat layer to the muscles, while the second instance, between 5.9 seconds and 7.05 seconds, illustrates the knife's movement back from the muscles to the fat layer. Additionally, it was noted that the average force level decreased when cutting through the muscles, aligning with the findings reported by Aly et al. (2023) (Aly, Low, Long, Brett, et al., 2023). The muscle-cutting region lies between the two peaks of the interface crossing.

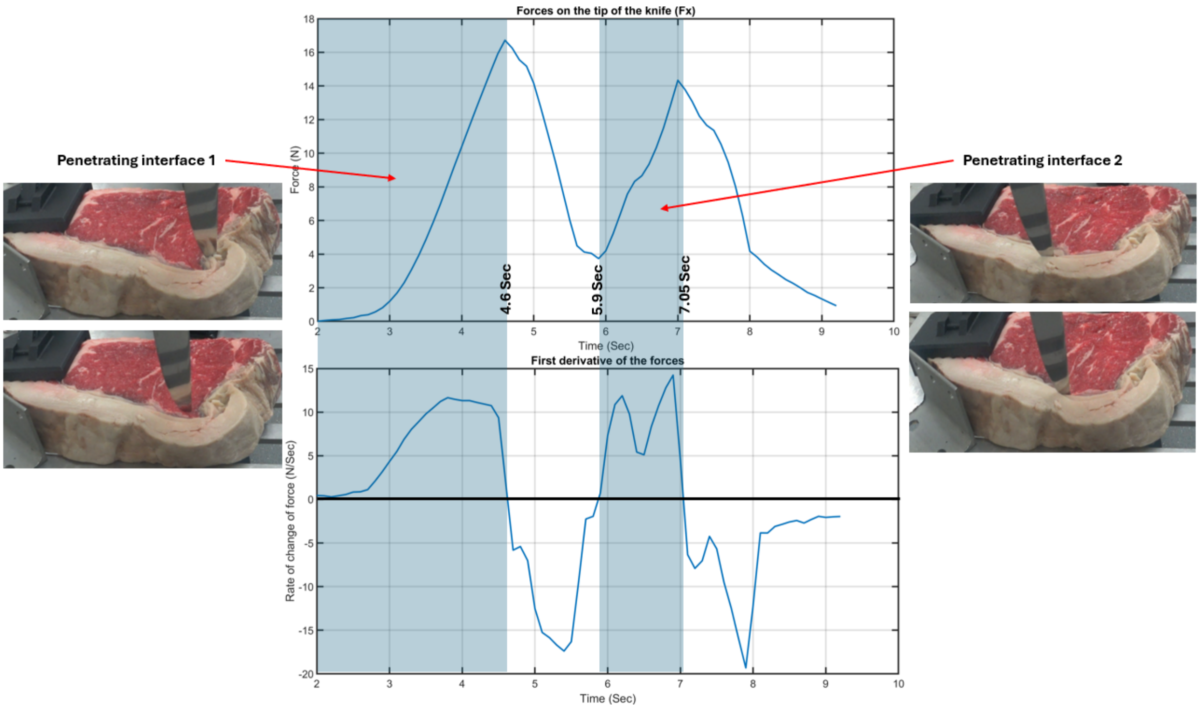


Figure 54: Force transients in the X-direction showing the instances of interface penetration for cutting path in Striploin 3

The side forces accurately represented the lateral forces resulting from tissue deformation around the knife and the structural layers within the sample that affected the knife's trajectory. As the cutting commenced, with the knife crossing interfaces from the fat layer towards the muscles, the side forces acting on the knife depicted tissue deformation. In region 1, where the knife crosses the interface from the fat layer towards the muscles, the tissues rotated, exerting pressure on the inner side of the knife. This rotation led to a positive increase in the rate of change of the lateral force derivative, indicating that the net lateral forces were higher on the inner side of the knife (region 1 in Figure 55). Region 1 ended at 4.6 seconds when the knife successfully crossed the interface and began cutting through the muscles.

In Region 2, from 4.6 to 7.05 seconds, the knife cut through the muscles in close proximity to the intermediate interface between the fat and the muscles. This positioning caused the interface to exert pressure on the outer side of the knife, as illustrated in region 2 in Figure 55. In the latter part of region 2, from 7.05 to 7.7 seconds, although the knife crossed back to the fat layer, it encountered a natural gap between the fat layers. This prolonged the force on the outer side of the knife, resulting in a slight deviation from its straight trajectory. In Region 3, the knife continued cutting through solid fat, with the net side forces from the side of the interface, the inner side of the knife.

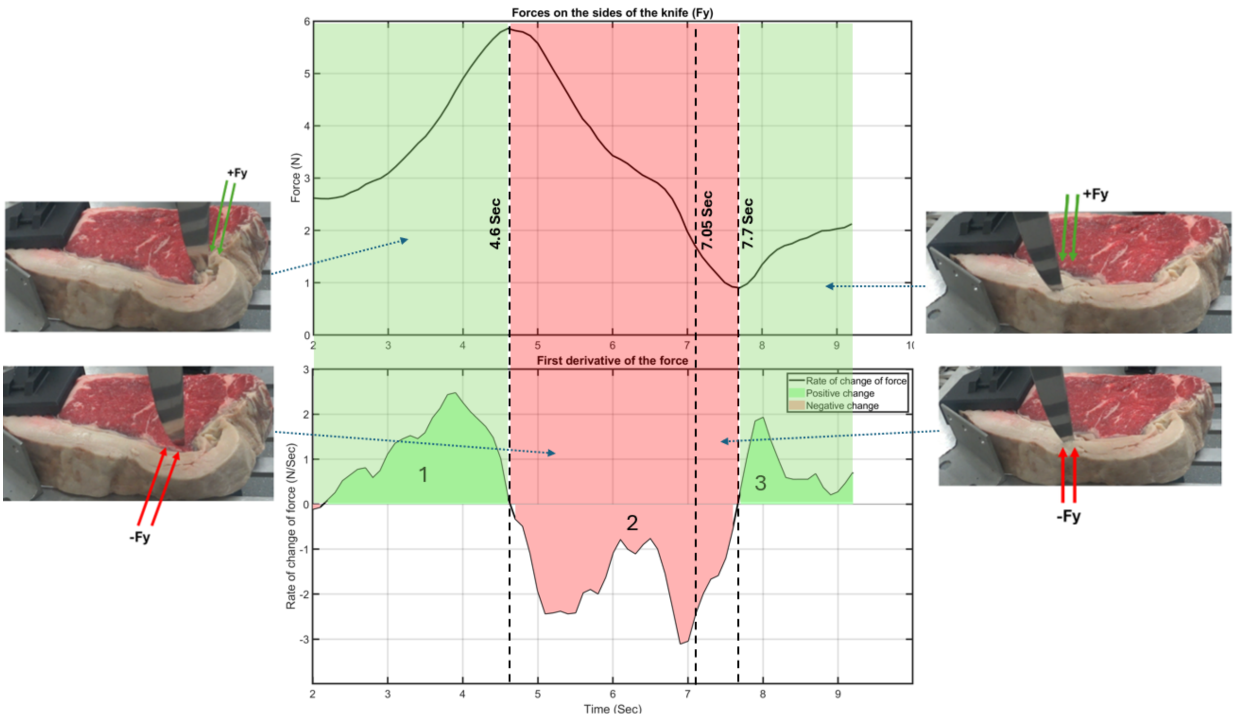


Figure 55: Force transients in the Y-direction showing the effect of the tissue behaviour and distribution on the lateral forces for the cutting path in Striploins 3

The cutting path in striploin 4 exhibits a trajectory that traverses across the fat layer, gradually converging towards the natural path between the layers within the sample. Consistent with the observed trends in other cuts, the lateral force transients follow a similar pattern along the trajectory. Initially, there is a force exerted on the inner side of the knife where the sample is held. Subsequently, there is a discernible gradient shift in the lateral force, indicating a change in the direction of the effective force towards the outer side of the knife as it approaches the interface. This shift is facilitated by the increasing compressibility of the meat as the knife moves closer to the interface and cuts towards it. Upon penetration of the natural gap between the fat layer, the cutting direction is dictated by the contour of the gap. The dynamics of the force transients are illustrated in Figure 56.

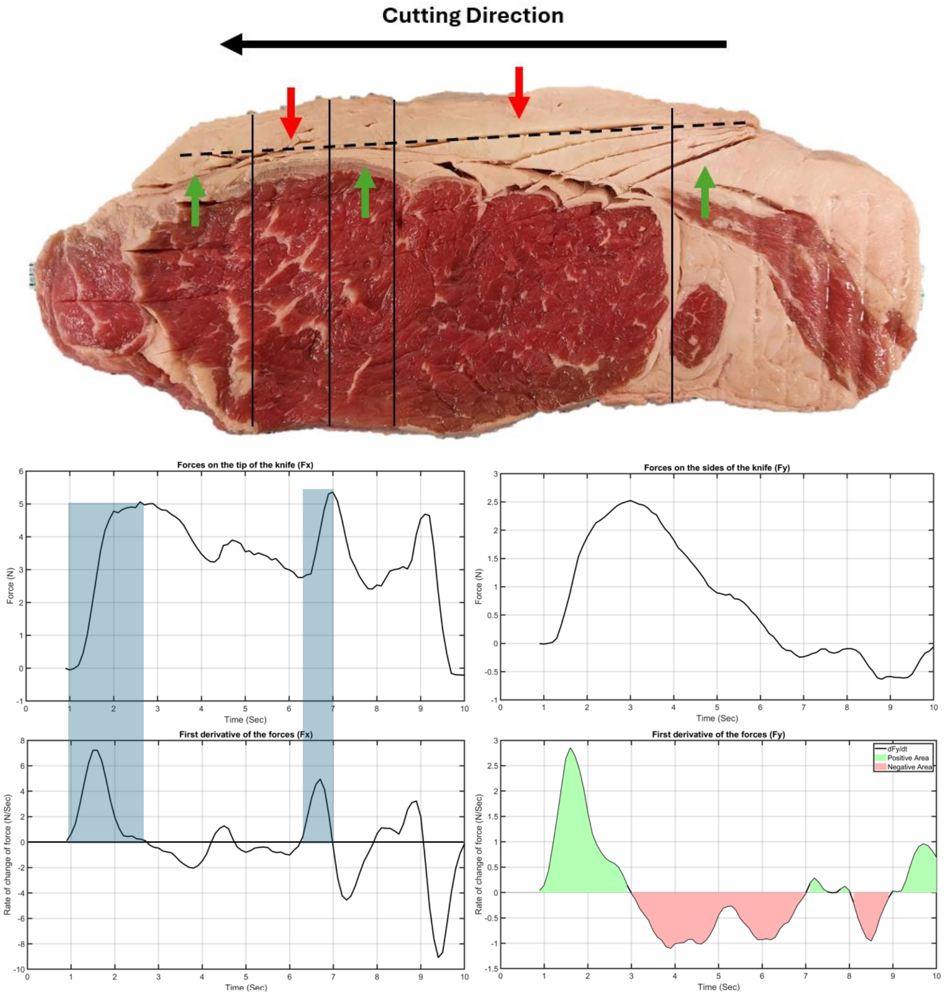


Figure 56: Force transients of F_x and F_y for the cutting path in striploin sample 4

5.2.4. Conclusion

Section 5.2 presented the results of additional experimental runs conducted during the study of trimming fat from striploin steaks. The results were based on the interpretation of the unique force transients of the force components on the tip of the knife (F_x) and the forces on the sides of the knife (F_y) and their rate of change (dF/dt). The correct interpretation of these force components, both individually and combined, provides invaluable information about the behaviour of the tissues surrounding the knife and the location of the knife at key cutting moments. This understanding allows for real-time adjustments to optimise cutting efficiency by adapting to varying tissue resistances.

The force on the tip of the knife showed the resistance accumulated on the cutting edge of the knife in the direction of motion. The main observation consistently realised across all cuts was that the rate of change of F_x typically increases when the knife approaches an interface or an air gap due to tissue deformation, necessitating extra force to overcome the resistance and manage to cut through the interface or air gap. On the other hand, the side forces F_y, representing the net lateral forces on the knife, provided insights into the tissue behaviour surrounding the knife. F_y and its rate of change, dF_y/dt, indicated how the lateral forces change over time, with shifts in dF_y/dt suggesting changes in tissue resistance and the effective direction of forces.

This chapter successfully confirmed the capability and accuracy of force transients in reflecting key cutting events, material features, and tissue behaviour around the knife across all twelve cuts, despite their differences. The force transients consistently provided insightful data, validating their effectiveness in various cutting scenarios.

In the ten cutting paths that progressively approached the interface in striploin samples 1 and 2, cross-correlation analysis effectively revealed whether the knife was cutting away or approaching interfaces. The results showed a decrease in the cross-correlation coefficient as the knife approached the interface area due to the increasing disturbance between the perpendicular force components (F_x and F_y) near the lean/meat interface. This aligns with the observations and results in Subsection 3.1, "Force Transients on the Approach to Tissue Interfaces," of Section 5.1.

In cutting paths 1, 2, and 3 from striploin samples 1 and 2, which traversed the fat tissue away from the fat/lean interface, both F_x and F_y reliably indicated when the knife was nearing the edge of the fat layer. The results showed that the point of maximum net force on the inner side of the knife from the lean/fat interface direction, coupled with a decreasing trend of the force on the tip of the knife, indicates that the knife is exiting the fat layer. At this point, the knife should rotate inward to prevent exiting, demonstrating the practical application of these force components in guiding precise cutting. Figure 57 shows an example of the position of the knife when these conditions are met.

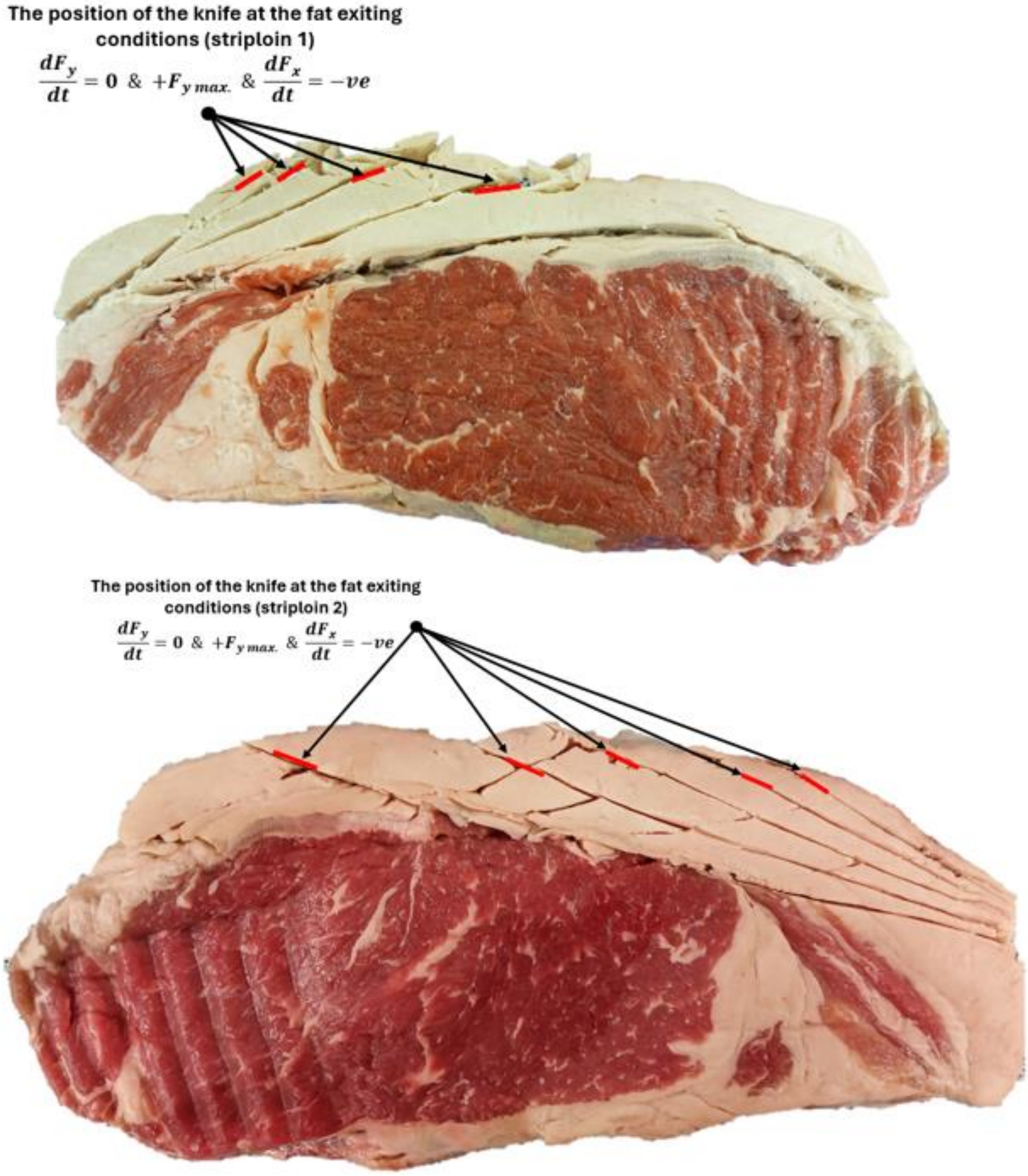


Figure 57: The location of the knife at fat exit conditions from the fat layer of striploins 1 & 2

In cutting paths 4 and 5 from both striploin samples 1 and 2, as well as in the cutting paths from striploin samples 3 and 4, the lateral forces accurately reflected the tissue behaviour on the sides of the knife. One observation was that the direction of the effective forces shifted towards the fat tissue when the knife encountered more deformable meat tissues on one side and stiffer fat tissues on the other. Another observation was that when the knife entered a natural path between the fat layers, the shifts in the forces on the sides of the knife accurately represented the contour of this path. This indicates the potential to follow the path if an appropriate automatic control strategy is applied. These observations support the findings presented in Subsection 3.2, "Interpretation of Force Transients," in Section 5.1, confirming the lateral forces' responsiveness to tissue variations and their utility in maintaining cutting accuracy along interfaces.

CHAPTER 6: IMPLICATIONS OF THE RESULTS AND FUTURE WORK

This thesis has explored machine tactile perception techniques for integration in automated beef processing. The techniques aim to discriminate tissue features in the carcass and cutting events related to the performed task. Unlike automated processing of workpieces in many other industrial sectors, there are substantial spatial and mechanical property variations and deformations in response to cutting forces encountered between workpieces in beef processing. The developed technique aims to discriminate meat tissue interfaces. This is crucial for tissue separations and deboning processes that involve producing products, where a machine must follow tissue interfaces or anticipate their approach. Using the approach described in Chapters 3, 4 and 5 for machine tactile sensing and the suggested cutting strategy of slicing fat layer from striploin steak product in Chapter 5, an automated system can be set up to discriminate a tissue interface encountered on a starting cutting path and then guide the knife along the interface. In this sense, the research has established a generic approach for cutting meat relative to the real-time position of meat tissue along the tissue interface. This approach accounts for expected natural variations and the significant deformations that occur in response to cutting forces.

Tactile sensing has been shown to be appropriate for cutting meat tissue interfaces. This is particularly relevant when the interfaces and the tissue response are externally invisible. However, the literature review of Chapter 2 showed that the previous work relied on tactile sensing for detection by force measurement value alone was not a robust approach. Instead, Chapters 3 and 5 have shown that the interpretation of force transients with an understanding of how these are related to meat tissue interface presentation is a reliable scheme to aid perception of the cutting dynamics.

There is a similarity with skilled human operators who guide cutting. They rely on detecting changes in knife reactive forces, which are interpreted based on their expectations of the tissue to be encountered. This understanding informs their cutting path. The expectation is based on previous experience in physical skill development and the knowledge of tissue configuration with respect to the anatomy of the animal. Just as an operator will need to develop new perceptions and skills for new cuts, we can expect adjustments in machine perception to be needed to process new operations.

In this chapter, the findings from the experimental work will be contextualised within the wider field of automated red meat processing. We will discuss the benefits this technology offers to the industry and how the work fits and aligns with future work in the field to develop control systems and technology implementation readiness.

6.1. Tactile perception for tissue-guided robotics in beef processing

A red meat carcass comprises three primary mediums for cutting: bones, fats, and muscles interspersed with connective tissues. The butchery process generates various cuts, categorised based on their relation to these mediums by following tissue interfaces when cutting (Figure 58):

- **Muscle from muscle cut**: Involving the separation of muscle from adjacent muscle along natural connective tissue seams and tissue interfaces, these cuts focus on isolating individual muscles or muscle groups for steaks or roasts.
- **Muscle from bone cut (deboning):** This essential butchery technique separates muscle from bone at the tissue interface, aiming to produce boneless cuts ideal for specific cooking styles. Skilful deboning maximises muscle retention while minimising waste.
- **Fat from muscle (that includes the trimming processes):** This process involves removing excess fat from muscle tissue. Trimming varies in extent, influenced by desired fat content in the final product. Often achieved through a slicing operation to identify and follow with given proximity to the tissue interface, it is a key final stage in product preparation.
- **Bone from bone (joints):** This refers to separating bones at the joints. This process is used for preparing cuts where the joints themselves, or the meat around them, are the focus. It is commonly seen in cuts such as oxtail, where the joints are part of the culinary appeal, or in preparing certain roasts, where the joint is removed for easier carving.

These cutting categories highlight a consistent principle in beef butchery: the importance of the capability to follow interfaces, or natural seams, between tissues. The definition of the seam between tissues from observations, conversations with skilled operators and personal experience can be identified as the natural line between groups of tissues within a carcass. It is a crucial landmark used to guide the cutting process. Following these less resistant pathways enables the efficient dissection of carcasses into various cuts with minimal waste. When cutting meat, the force required at the cutting edge of the knife is reduced along these less resistant pathways, as the cutting edge can more easily navigate through the softer connective tissue and fat that make up these seams. The same is true for the sides of the knife, which encounter friction as they slide through the meat. The value of frictional resistance experienced during cutting is a function of the density and texture of the meat. In areas where the meat is more dense or tough (such as within the fat tissues or muscles), the value of frictional resistance is greater. Conversely, along seams (the pathway of least resistance), where muscle tissue is less dense and with greater occurrence of connective tissue or fat, the frictional force component is lower, easing the progress of the knife along the cut path.

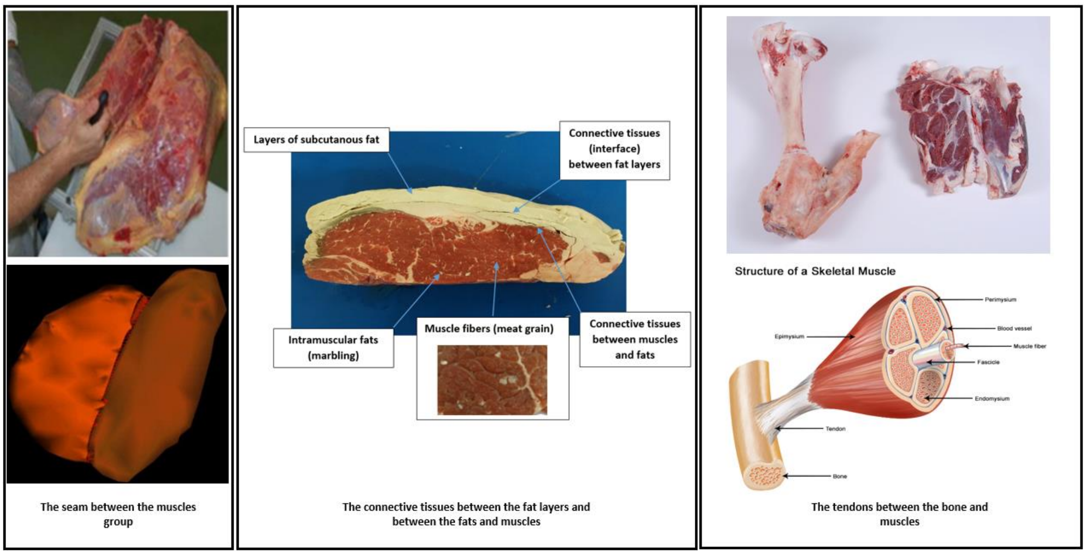


Figure 58: Types of interfaces between different tissues

The technique can be used to significantly enhance automation capability in abattoir cutting operations. Chapter 4 showed the ability of the tactile perception technique to trim individual pieces of striploin steaks precisely by following interfaces in the product. This advanced capability for automation presents a unique opportunity for abattoirs: the production of intricate added-value cuts, such as striploin steaks, traditionally associated with butcher shops. The introduction of a specialised machine capable of processing the loin primary cut into individual steaks and performing precise trimming is not normally considered in abattoir operations. This innovation diversifies the abattoirs' product range by offering substantial labour savings.

The tactile perception approach has potential application to a wide range of cuts. For example, this method could be used to separate the round muscle into three major muscle groups: inside, thick flank, and silverside. The beef round has a visually detectable seam between the muscle groups (Figure 59). As outlined in Chapter 2, previous research has targeted this specific cut, attempting to follow the muscle seams primarily using vision and simulation (Long et al., 2014a). A force sensor was deployed on a pulling robot to stretch the interface ahead of the cutting knife. However, this approach was unsuccessful due to the absence of a real-time adaptive sensing technique capable of reacting to unexpected resistive forces, which prevented the robot from completing the cut.

The sensing technique proposed in this thesis can rectify these issues by replacing the vision and simulation components previously used to guide the cutting knife. As substantiated in Chapters 2 and 3, one of the critical advantages of the tactile perception technique is its precision in detecting increases in resistive force and responding accordingly, either by oscillating the knife or reorienting it to maintain the correct cutting trajectory. This method is more simple and computationally efficient without requiring simulation for trajectory tracking. The approach does not eliminate the use of vision and simulation techniques. Instead, that can be more usefully applied as supportive tools to enhance accuracy rather than as the primary method for guiding the knife.

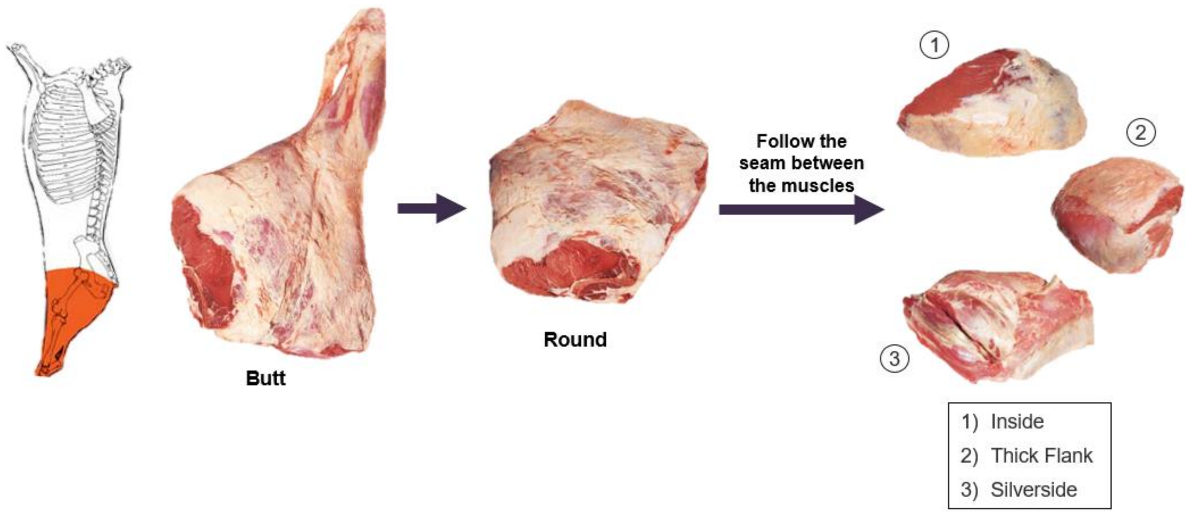


Figure 59: Separation of the round cut muscle groups

In deboning, where muscles are separated from bones, although the tissue types differ, the underlying concept remains the same, and is potentially easier due to the distinct properties between bone and muscle. The focus here is to maintain side contact with the bone without cutting into it and simultaneously avoiding penetration into the muscle seam.

It is critical to recognise the role of cutting tools and handling techniques, particularly when employing tactile perception in meat processing. The manipulation technique in the study was simple: the meat was secured against the knife, executing a slow, straight-line motion along a predefined trajectory. This was specifically applied to striploin steaks in the experimental setup. In practical settings, carcass handling and manipulation techniques become more significant. Carcasses are often hung in front of the operator during splitting and primary cuts, leveraging gravity for tissue separation. Smaller cuts are performed on benches, with manual manipulation by operators using techniques such as stretching and fixing the product in place for precise cuts.

Regarding cutting tools, static knives of various sizes and shapes are chosen for their suitability to the specific cut. Operators employ mixed movements, such as oscillating motions, to ease cutting, especially against increased resistance from meat deformation at interfaces. Sometimes, cuts are made at multiple depths, progressively deepening until complete. All these techniques are reactive responses to unique transient forces encountered during cutting.

Furthermore, the type and working mechanism of the cutting tool is crucial, especially when considering unique force transients and using non-static blades such as rotary, jet, or oscillating blades. Each tool type introduces different dynamics requiring analysis and adaptation for optimal performance.

6.2. Research outcome as part of future work

Chapter 2, the review chapter, revealed that varying characteristics and deformable nature of red meat require real-time perception to guide cutting tools relative to meat tissue position during processing. An approach for tactile sensing to discriminate tissue interfaces and anticipate deflection within the medium has not been established before. Tactile perception represents a largely untapped sensing method to aid machine perception in red meat processing, holding promise for real-time tool guidance during cutting operations. In this thesis, tactile data is examined from a novel perspective, drawing inspiration from the perceptual skills of human operators. Human operators interpret tactile data not as mere numerical values but recognise shifts and patterns, utilising this understanding to discriminate tissues and identify specific cutting events within a product, informed by their accumulated knowledge and experience.

The application of machine learning and pattern recognition techniques aims for automation machines imbued with human-like perceptual skills. By identifying distinct patterns in force data, such models can discriminate between tissues and tissue interfaces, thereby enhancing the precision and efficacy of automated cutting systems. Having correlated the nature of cutting force transients to the guiding tissue features of the cut path opens the possibility of developing machine learning and pattern recognition to guide a knife in red meat cutting. Additionally, exploring stochastic time series models like ARIMA could potentially model the temporal characteristics of cutting forces, providing another layer of predictive capability to enhance real-time tool guidance. These models can capture the underlying patterns and trends over time, which may further improve the understanding and prediction of cutting events.

The research conducted in this thesis represents the initial steps to developing machine learning and pattern recognition to guide a knife in red meat cutting. It involves data collection and labelling by recording the force exerted on the knife under controlled cutting conditions and correlating the unique force transients with crucial cutting events. For example, the experimental results show that cutting through different tissue types leads to noticeable force changes. Cutting across muscle requires less force compared to cutting through fat, and following along tissue interfaces requires minimal force due to weaker bonds between the tissues, a technique commonly used in manual cutting for blade guidance. Additionally, the lateral forces on the sides of the knife reflect the contours of tissue interfaces, suggesting their potential as a navigational aid.

The second step focuses on analysing and extracting features from this data that characterise the cutting scenarios. These features include the shape of the unique transients in the data indicative of certain cutting events. Features include the detection of peaks during interface penetration by monitoring the force rate change on the tip of the knife and the higher mean force required to cut through fat compared to muscle. Also, the direction of the meat pressure on the sides of the knife is represented by the direction of the rate of change of the lateral force component. These features are crucial for discrimination and enhanced precision in automated systems.

Subsequent steps involve pre-processing. In this research, simple noise filtering techniques, such as the moving average method and Savitzky-Golay filter, were applied. Other frequency-based filter methods remain to be explored, as distinct frequency patterns were observed while cutting different tissues. Normalisation was also critical to standardise data for consistent analysis, focusing on patterns over magnitude.

Further pre-processing is expected to be the next step to progress the work performed in this research. Time-domain analysis identifies peak forces, while frequency-domain analysis, using methods such as Fast Fourier Transforms (FFT), discerns the force pattern's frequency components. For non-stationary signals typical in meat cutting, time-frequency methods such as the Short-Time Fourier Transform (STFT) or Wavelet Transforms are effective (Sejdić et al., 2009).

Machine learning algorithms, such as support vector machines (SVM) and neural networks, are then employed to efficiently classify different types of cuts or textures. The accuracy and reliability of force measurements in automated meat cutting can be significantly enhanced by combining force sensing technology with intelligent data processing, such as neural networks. These algorithms are designed to draw on detailed pattern observations from previous studies, allowing for the discrimination of various tissue types and cutting events. For example, Maithani et al. (2021) illustrated a force amplification strategy and an intent prediction strategy using an unrolled Recurrent Neural Network (RNN), which enabled a KUKA LWR robot to provide assistive forces to a professional butcher (Maithani et al., 2021).

The applications of these signal processing techniques extend beyond just enhancing automated cutting systems. They contribute significantly to culinary training, food texture research, and even the design of more ergonomic and efficient cutting tools. This exploration into real-time signal processing of force transient data in meat cutting offers insights into the mechanics of cutting and potential improvements in automation and efficiency. Future research could delve into more advanced machine-learning techniques and improved sensor technologies for more precise analysis.

CHAPTER 7: Conclusion

A real-time machine tactile perception technique for automatically guiding a cutting tool attached to a robotic system for cutting red meat has been achieved in this work. The approach has utilised information in the temporal (time-series) sensory data to discriminate conditions and tissues in real-time through characteristic behaviours of the medium to enable guidance on the trajectory of the cutting path in the deforming meat tissues. The research findings have been applied to develop a simplified cutting strategy to guide a knife to slice a fat layer from the top of a striploin steak by cutting relative to the interfaces in the product.

The current state of robotics and automation in red meat and pork cutting and deboning and the applicability of existing sensing technologies for guiding robotic systems in real-time were reviewed and evaluated. The review identified the shortcomings and challenges of current robotics implementations, and the suitability of existing sensing technologies to guide robotic systems in real-time have been identified. Tactile sensing has not been used significantly, as using force values to discriminate working conditions in meat is unreliable. Yet, this sensing mode enables exact positioning between the cutter and the tissue, provided the tissue can be discriminated. The technique established here has accomplished this requirement.

A versatile industrially appropriate testing rig to identify tissue cutting force characteristics correlated with tissue presentation and the deformation taking place has been developed for the experiments. The rig included a 6-axis robotic manipulator, a 6-axis force sensor, a static knife mounted on a cabinet, and an integrated adjustable table for meat specimen. The food-grade and IP67-rated rig material enabled machine maintenance, and the setup was easily cleaned following experiments.

The robotic manipulator, selected for its suitable workspace and payload, proved to be well-suited for the experimental tasks. Adjustability and versatility in the table design enabled a wide variety of cutting trajectories and meat specimens to be attached to the cabinet, allowing enhancements by adding extra brackets, which were instrumental in securing and precisely positioning the test samples in front of the knife. The force sensor exhibited high sensitivity to all types of force components on the knife and its direction, which was critical for understanding the cutting dynamics. The precision was presented through the accurate real-time correlation between the force data from the sensor and the cutting events performed by the knife, ensuring accuracy in the observations and analysis. The implementation of high-resolution cameras enabled capturing of clear footage from various angles.

The test samples were chosen to allow observations and correlation of cutting action, tissue response and force transients in a frame approaching two dimensions.

The sample used was striploin steaks, where the tissues are almost constant through the thickness of the medium.

An approach to identify and discriminate key tactile characteristics of tissues and important structures to guide trajectories relative to meat tissue and tissue interfaces was achieved. The tactile sensing technique explored interprets characteristic transients in the tactile feedback data to discriminate between different tissues and tissue interfaces encountered during cutting and anticipate the approach to key structures during the cutting operation. When cuts were made across various tissues, there was significant precision when comparing the positions of the knife in the tissues, as observed in recorded cutting videos, to the force transients provided by the force sensor through the robot. Cutting through lean muscles exhibited lower average force requirements and smoother characteristic transients compared to the fat tissue layer, where additional interfaces surrounding air gaps are encountered within the tissue. The interface between these two primary tissues – muscle and fat – represents a critical transition zone, where the knife encounters the interface between them. The characteristic force transients here show a distinct shift between two levels of force values and a prominent peak attributed to deformation of the tissues responding in the presence of the elastic nature of the interface. An analysis of these force characteristics, when cutting across tissues with similar arrangements, revealed a high degree of consistency through cross-correlation analysis. Correlation coefficients ranged from 80% to 97% when similar cuts were performed on comparable tissue arrangements.

Controlling the depth of the knife in the tissues is a challenging aspect of cutting, both in manual and automated operations. This difficulty arises due to several factors: tissue interfaces inside are invisible from the outside of the meat sample, the non-uniformity of tissues, and varying relaxation rates of tissues influenced by temperature and gravity. Experimental work revealed that the depth of cutting using the knife impacts only amplitude values of force transients, not the observed characteristics of the different stages of cutting. Force pattern analysis showed substantial similarity across different cutting depths (10, 20, and 30 mm from the sample surface), with cross-correlation coefficients ranging from 88% to 97%.

Formalisation of techniques for discriminating tissues, tissue interfaces, and the meat's response have been achieved, along with a cutting strategy proposed to perform a simplified version of cutting a typical marketable product (Striploin trimming). The approach was tested on striploin steak trimming task by following interfaces. Two orthogonal forces transients were used, leading knife edge cutting force and side force. The methodology effectively indicated when the knife was approaching and cutting through an interface. The leading edge force transient was employed to identify when the knife is approaching an interface, while the side force transient was used to delineate the contour of the interface being followed, as evidenced by the meat pressure on the sides of the knife.

Visual observations, supported by formal cross-correlation and dynamic time warping (DTW) analyses, showed stronger similarities in the orthogonal force transient components for paths in uniform parts in the fat layer further from any interfaces, yielding cross-correlation similarities of 95% and 97%, and DTW scores of 1.2 and 2.6. However, as ascutting approached the interface, the correlation weakened due to disturbances and tissue breakdown at this critical juncture. In these instances, the cross-correlation dropped to 79%, and the DTW score increased to 5.76. Pearson correlation analysis for cuts near the interface indicated a decline in correlation as the knife neared and sliced through the interface, particularly between fat layers near the main fat/lean interface. Concurrently, the side forces demonstrated high sensitivity and precision in response to pressure exerted by tissues against the sides of the knife.

The research contribution lays down a practical framework for the real-time application of tactile sensing in meat processing. The findings indicate that when enhanced by tactile sensing, machine perception can successfully navigate the complexities of meat cutting, a task characterised by variations in carcass presentation and mechanical properties.

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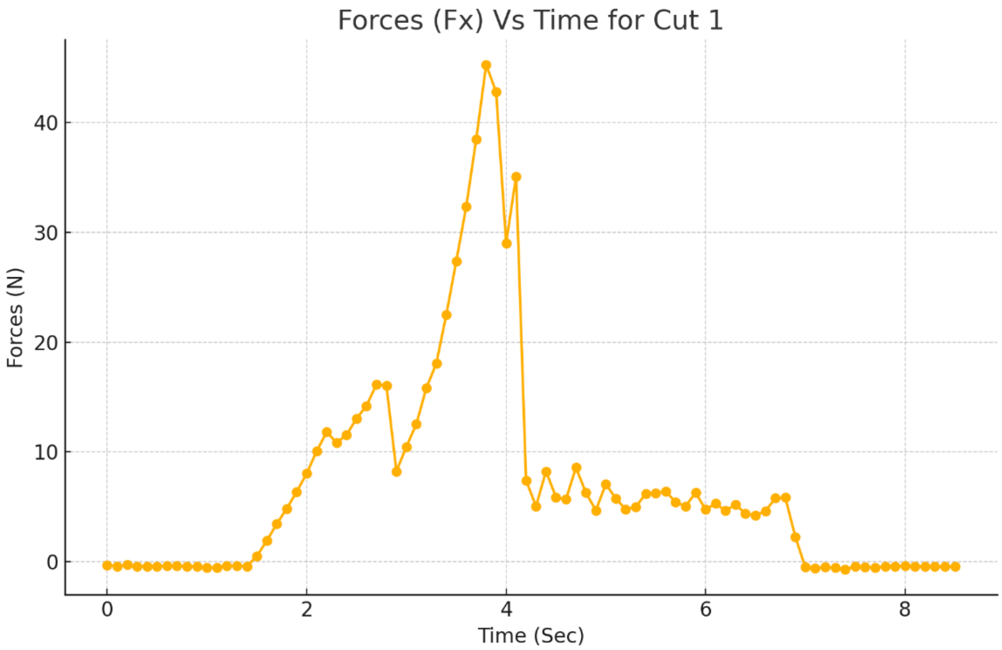
APPENDIX A: GRAPHS OF ALL RAW DATA

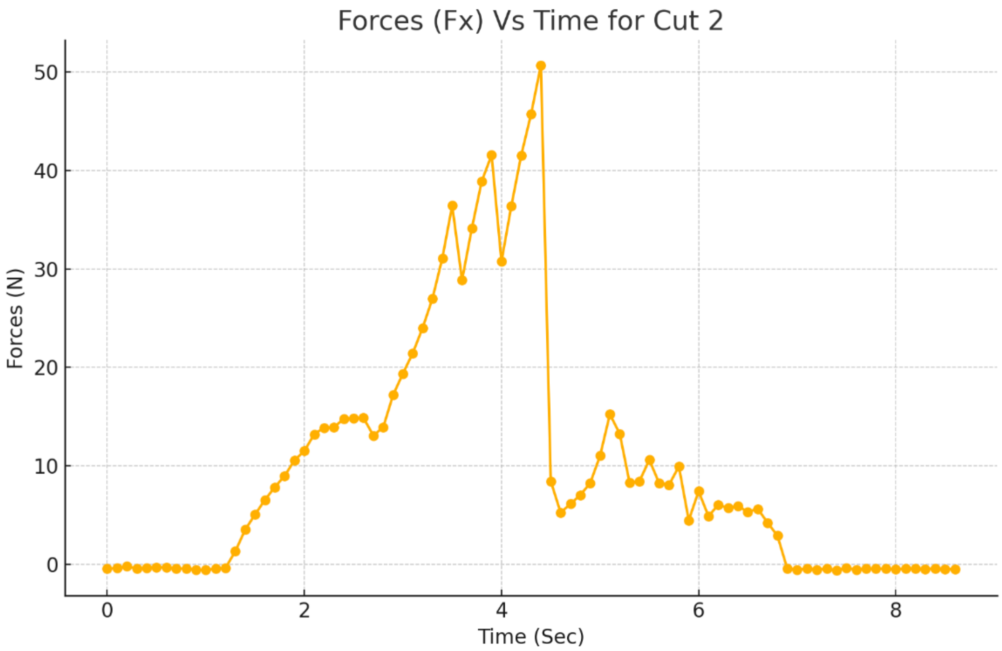
This section presents the graphs of all the raw data for all the experiments. The cuts are divided by chapters.

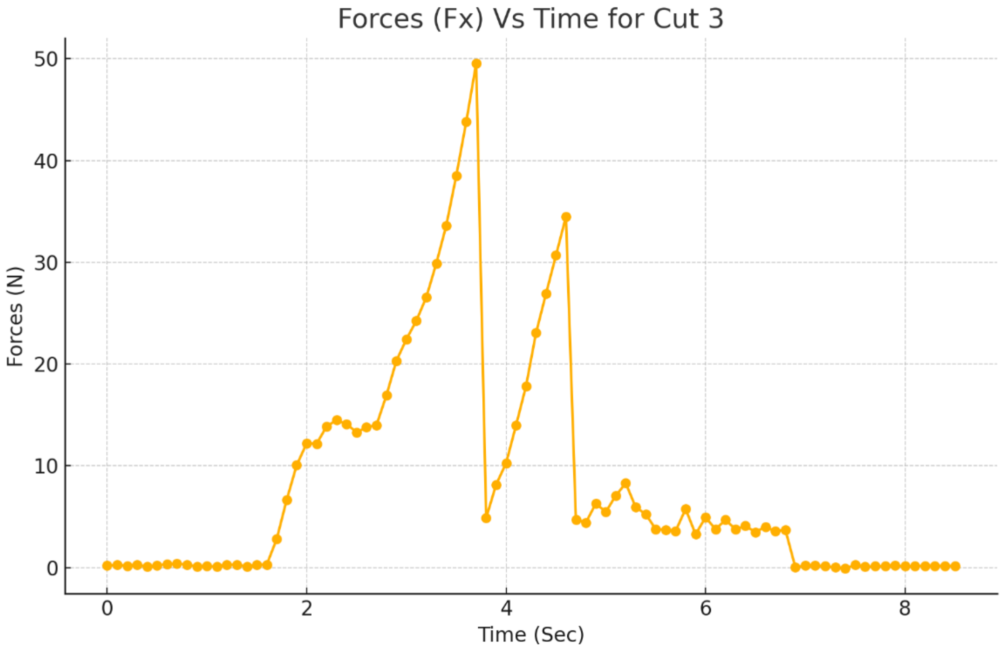
A.1. Chapter 4 data (Sections 4.1 and 4.2)

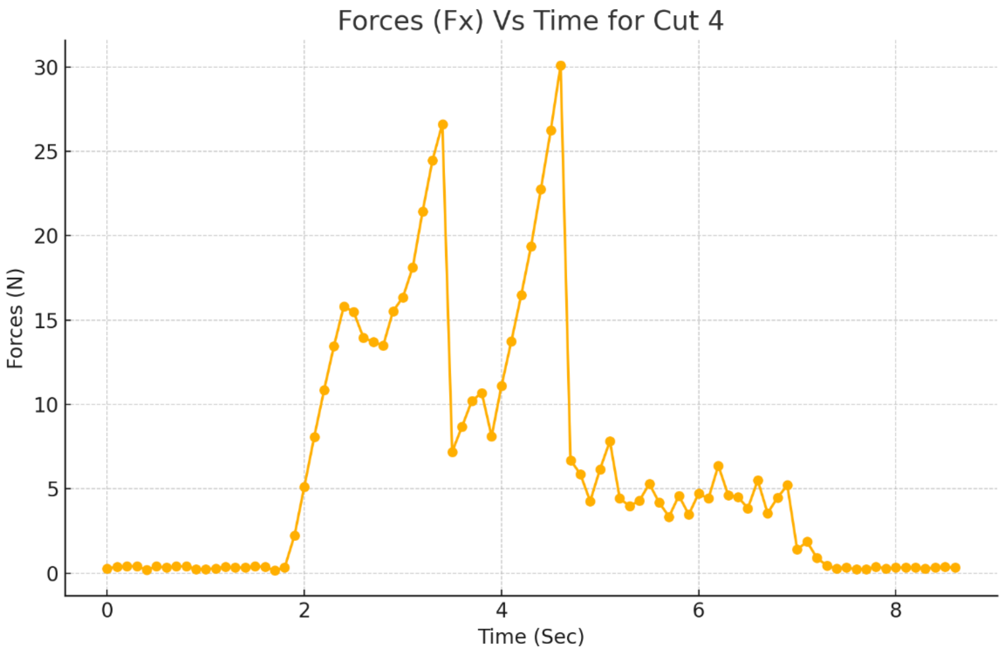
A total of 24 cutting paths were conducted. Of these, 18 were part of the investigation presented in Chapter 4.1, and 6 were part of Chapter 4.2. Eight cuts were performed as straight-line cuts across the tissues from the fat layer towards the muscles, and another 8 were performed in the opposite direction. Six cuts were performed at different cutting depths: 10, 20, and 30 mm.

A.1.1. Cutting paths directed from the fat layer towards the muscles

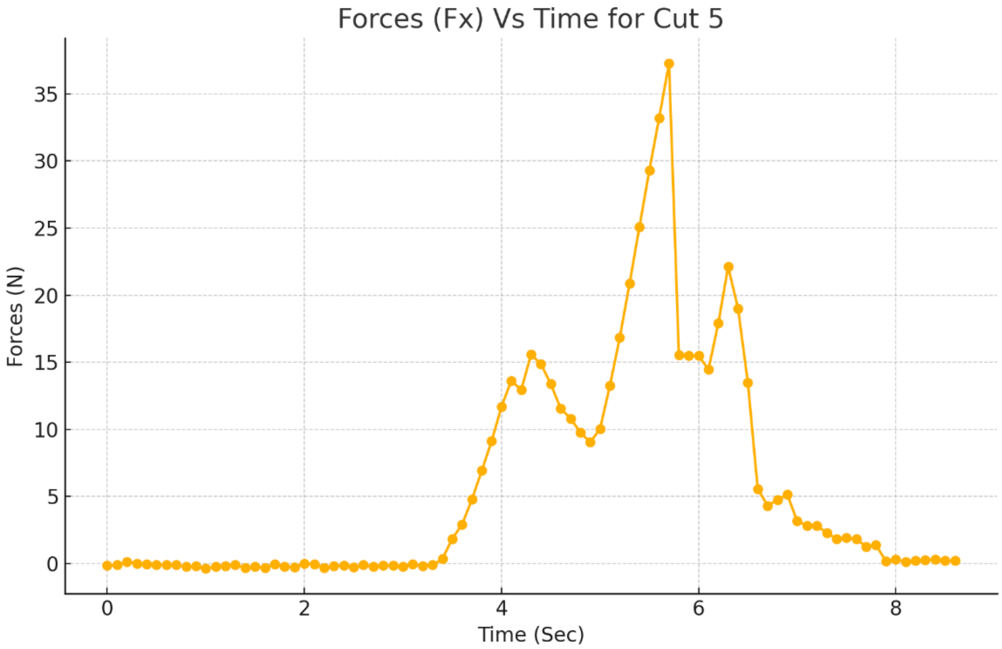



Forces (Fx) Vs Time for Cut 2
Forces (N)
Time (Sec)
0
10
20
30
40
50
0
2
4
6
8

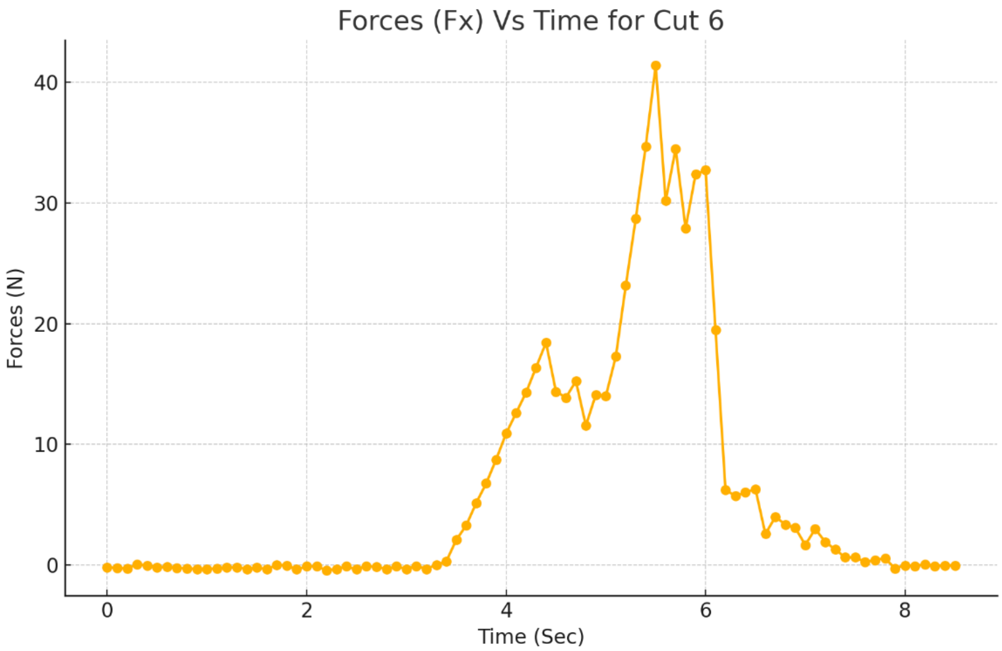

Forces (Fx) Vs Time for Cut 3
Forces (N)
Time (Sec)
0
10
20
30
40
50
0
2
4
6
8

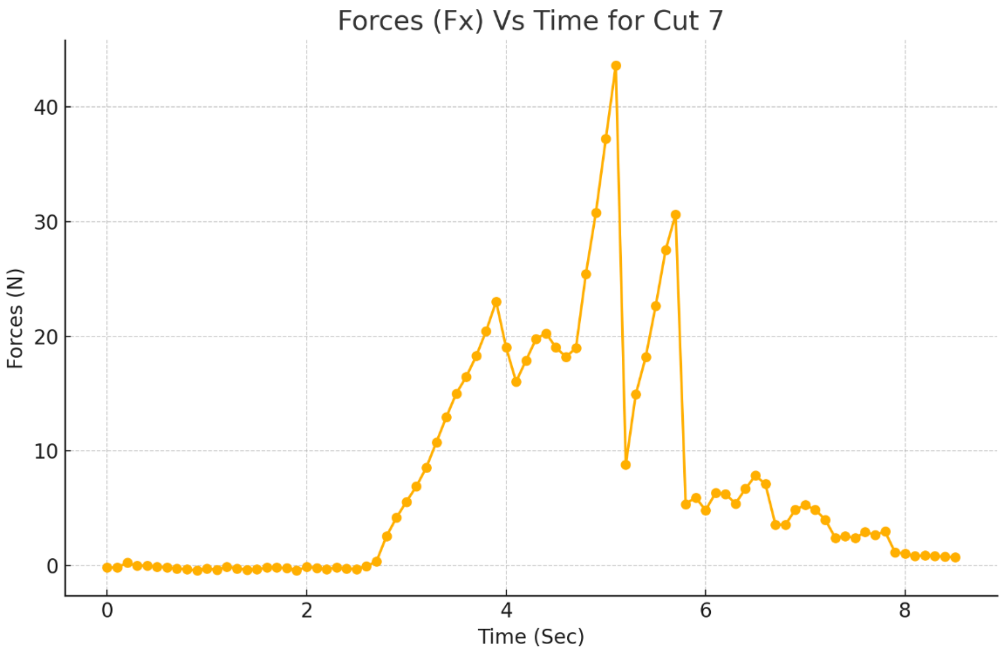


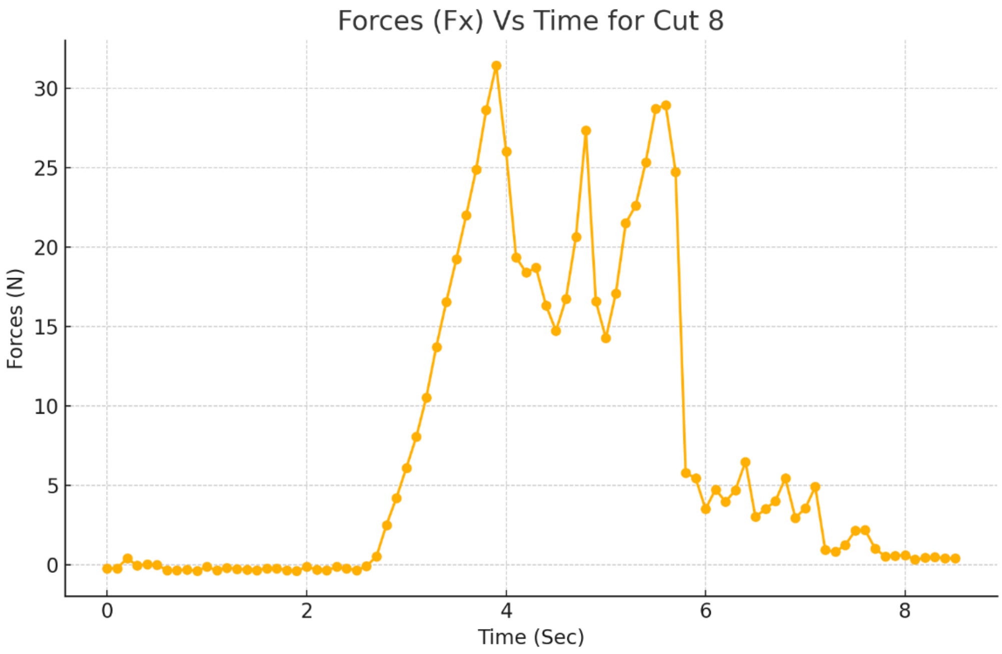
Forces (Fx) Vs Time for Cut 4
Forces (N)
Time (Sec)
0
5
10
15
20
25
30
0
2
4
6
8

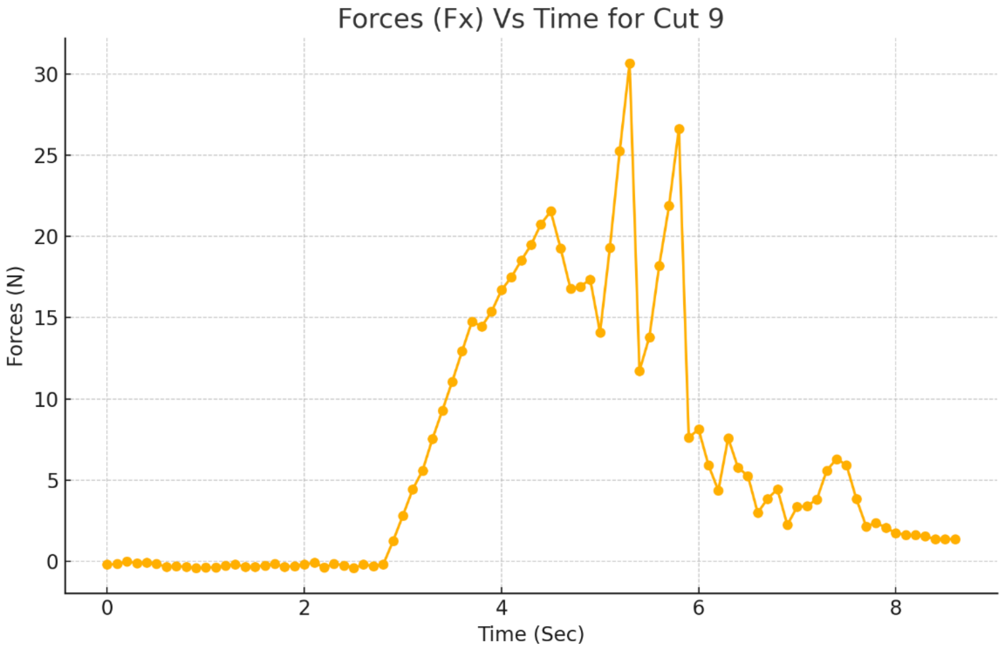


Forces (Fx) Vs Time for Cut 5
Forces (N)
Time (Sec)
0
5
10
15
20
25
30
35
0
2
4
6
8

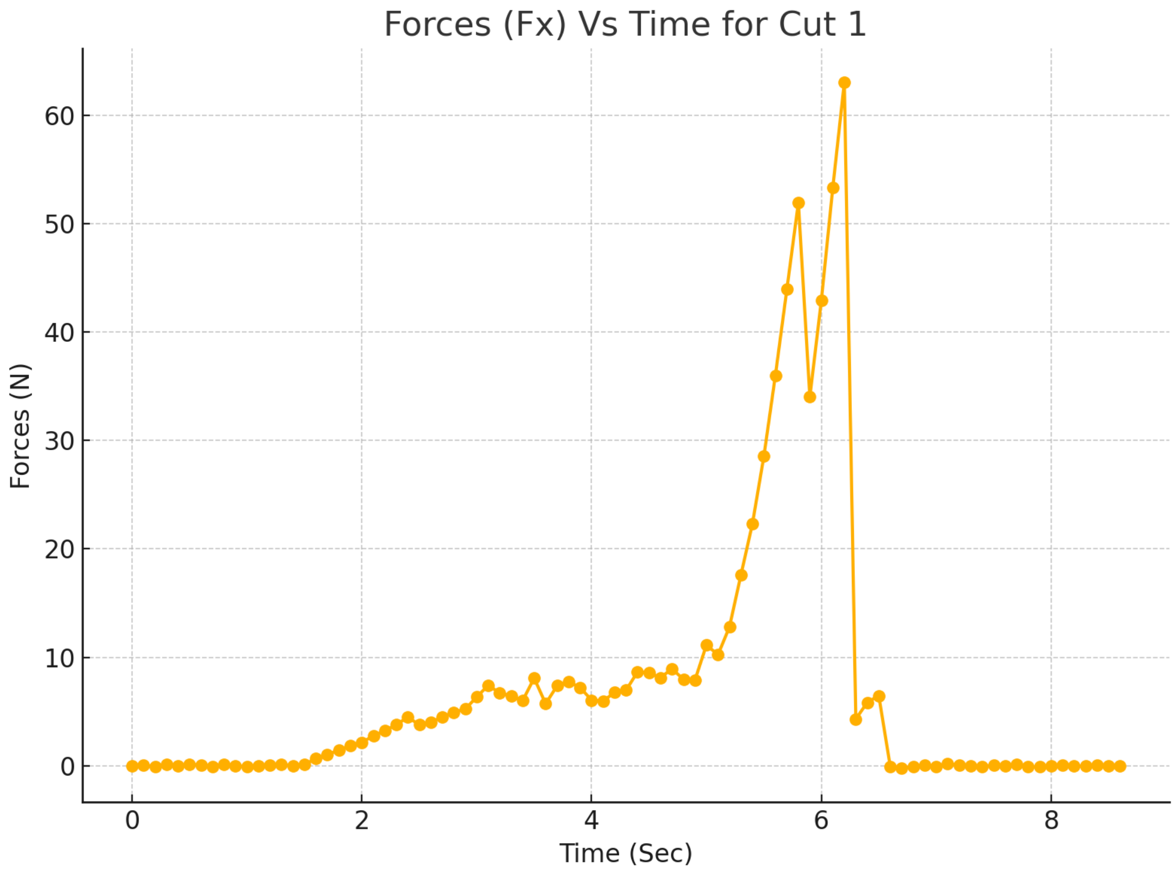

Forces (Fx) Vs Time for Cut 6
Forces (N)
Time (Sec)
0
10
20
30
40
0
2
4
6
8

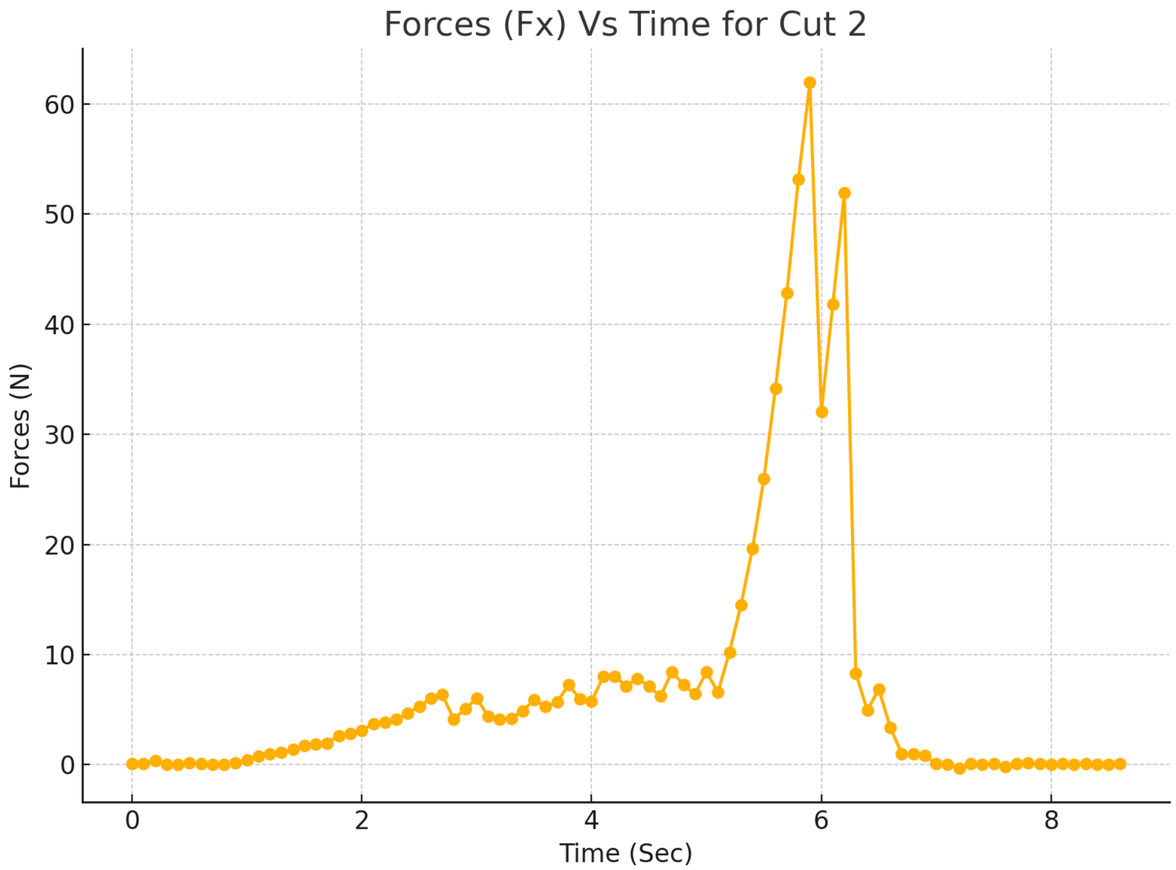

Forces (Fx) Vs Time for Cut 7
Forces (N)
Time (Sec)
0
10
20
30
40
0
2
4
6
8


Forces (Fx) Vs Time for Cut 8
Forces (N)
Time (Sec)
0
5
10
15
20
25
30
0
2
4
6
8

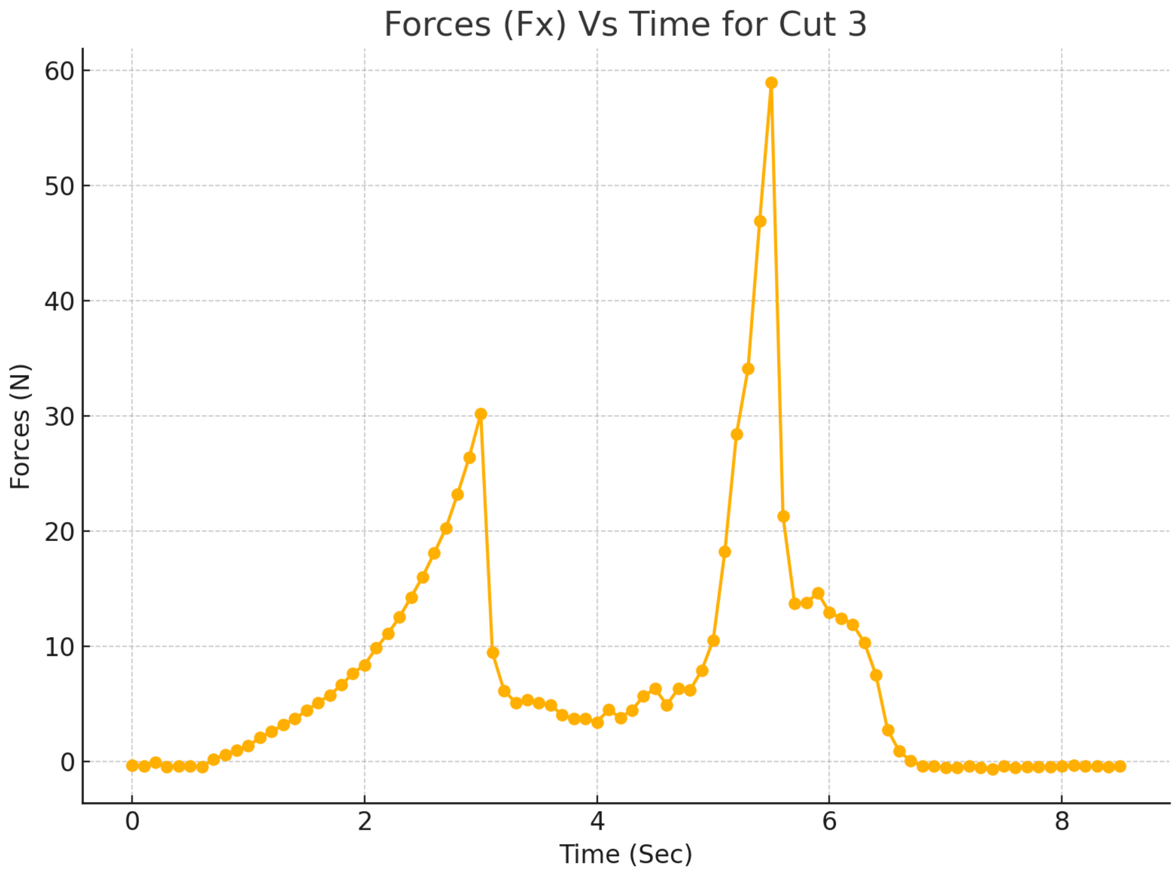

Forces (Fx) Vs Time for Cut 9
Forces (N)
Time (Sec)
0
5
10
15
20
25
30
0
2
4
6
8

A.1.2. Cutting paths directed from the muscles towards the fat layer

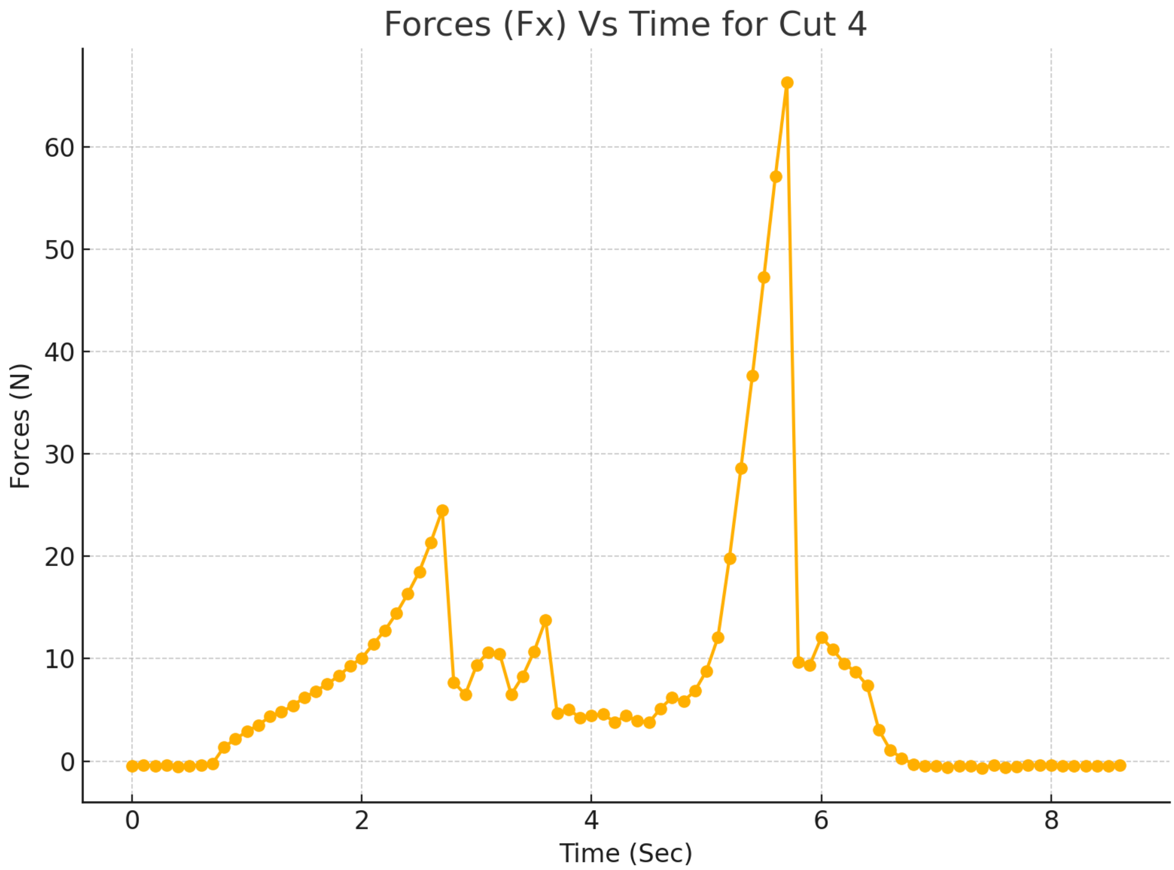


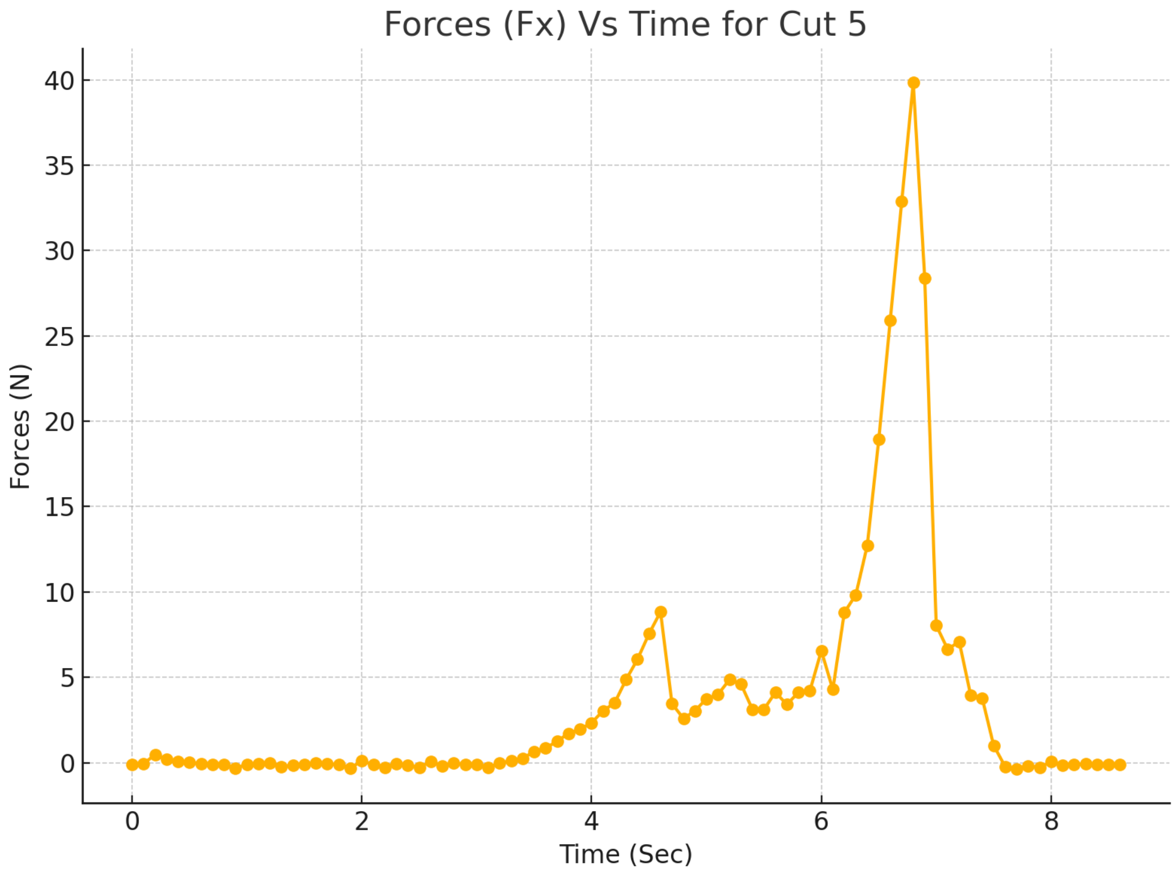


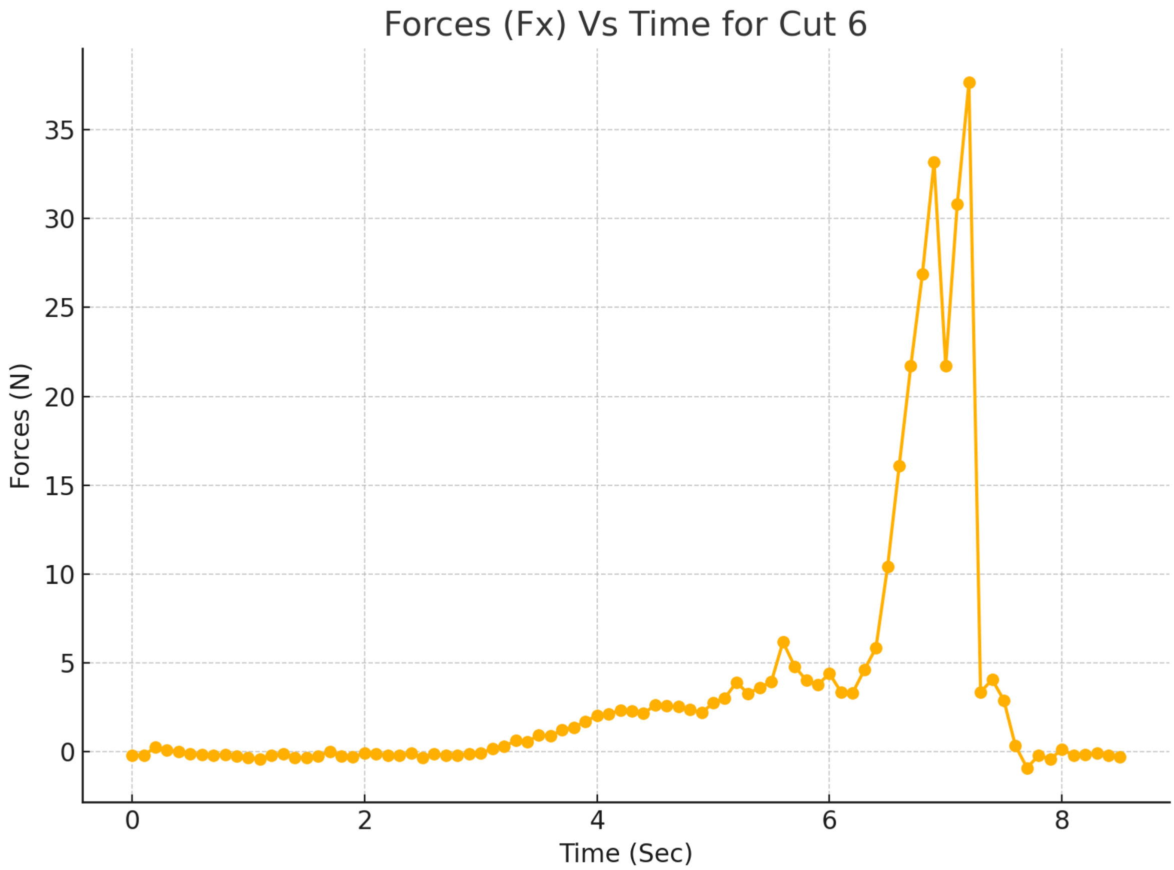
Forces (Fx) Vs Time for Cut 2
Forces (N)
Time (Sec)

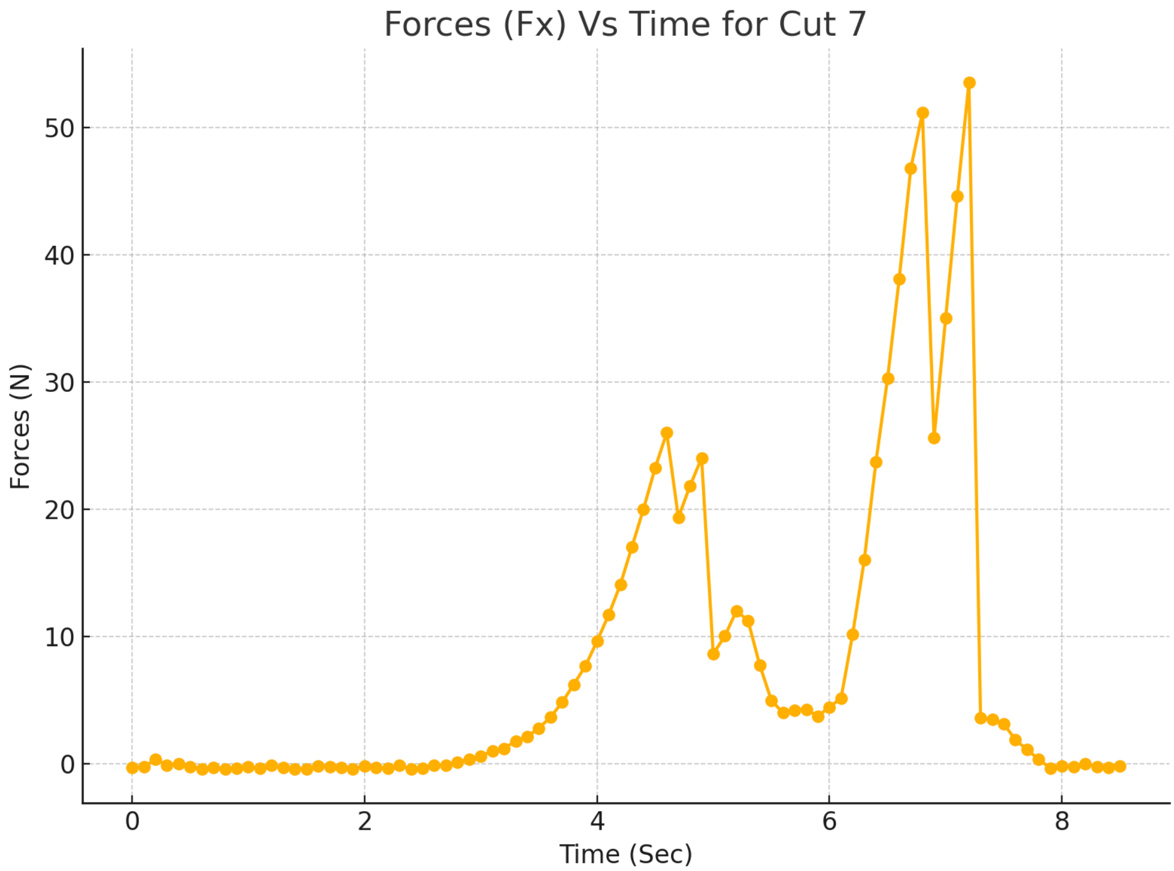


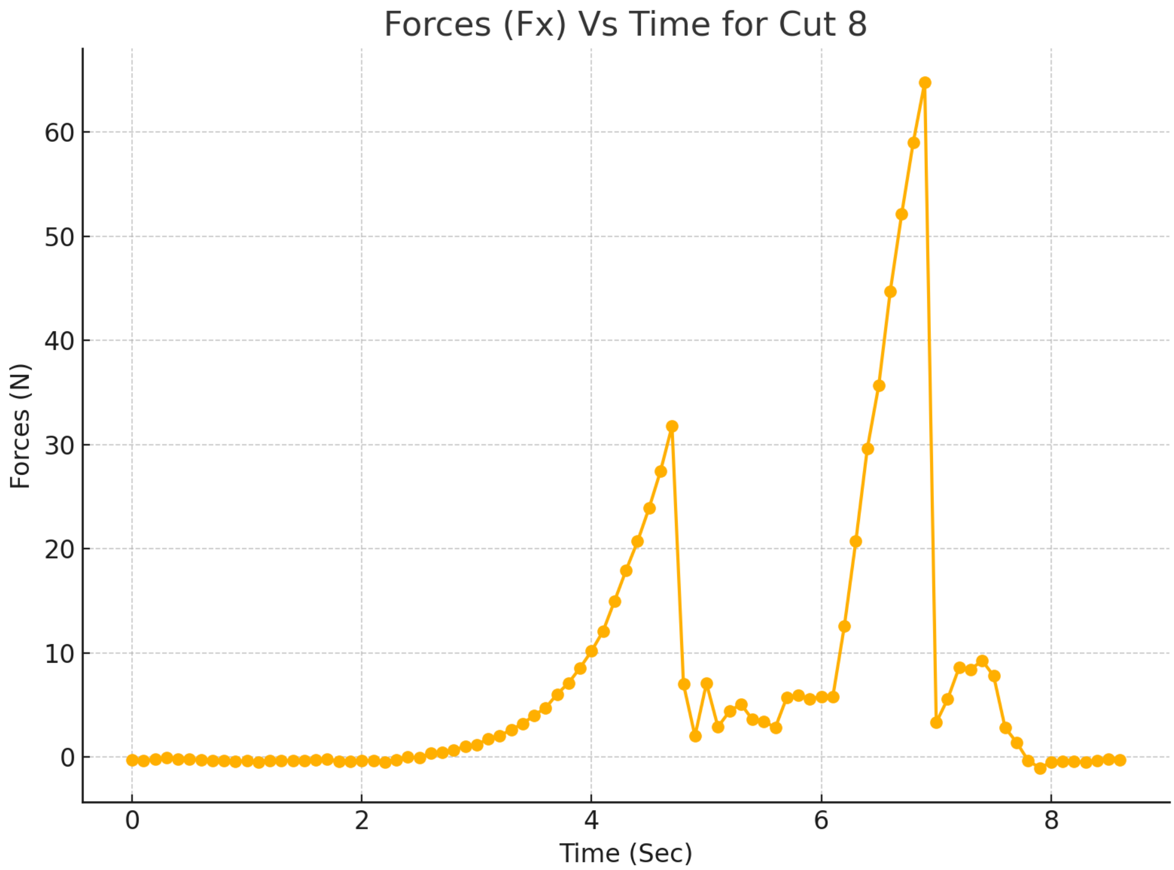
Forces (Fx) Vs Time for Cut 3
Forces (N)
Time (Sec)


Forces (Fx) Vs Time for Cut 4
Forces (N)
Time (Sec)
0
10
20
30
40
50
60
0
2
4
6
8

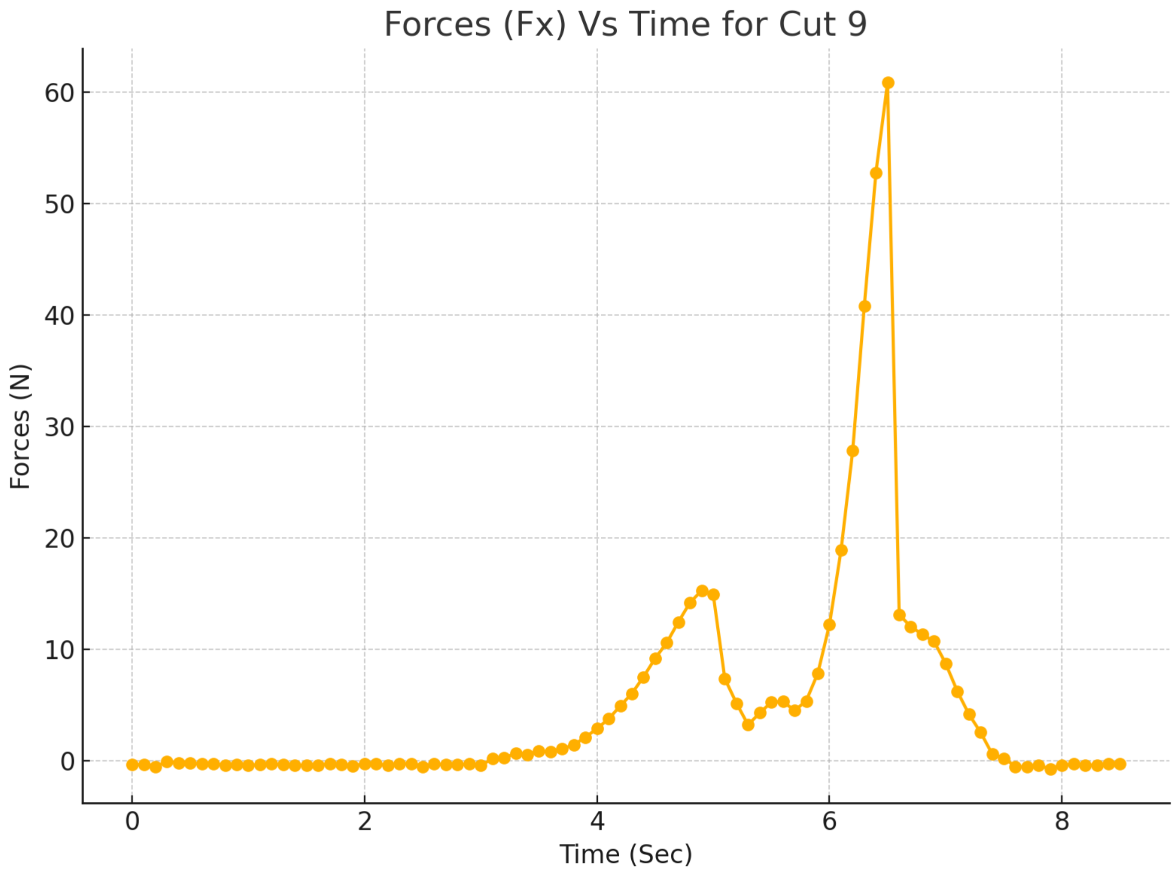

Forces (Fx) Vs Time for Cut 5
Forces (N)
Time (Sec)
0
5
10
15
20
25
30
35
40
0
2
4
6
8


Forces (Fx) Vs Time for Cut 6
Forces (N)
Time (Sec)
0
5
10
15
20
25
30
35
0
2
4
6
8


Forces (Fx) Vs Time for Cut 7
Forces (N)
Time (Sec)
0
10
20
30
40
50
0
2
4
6
8

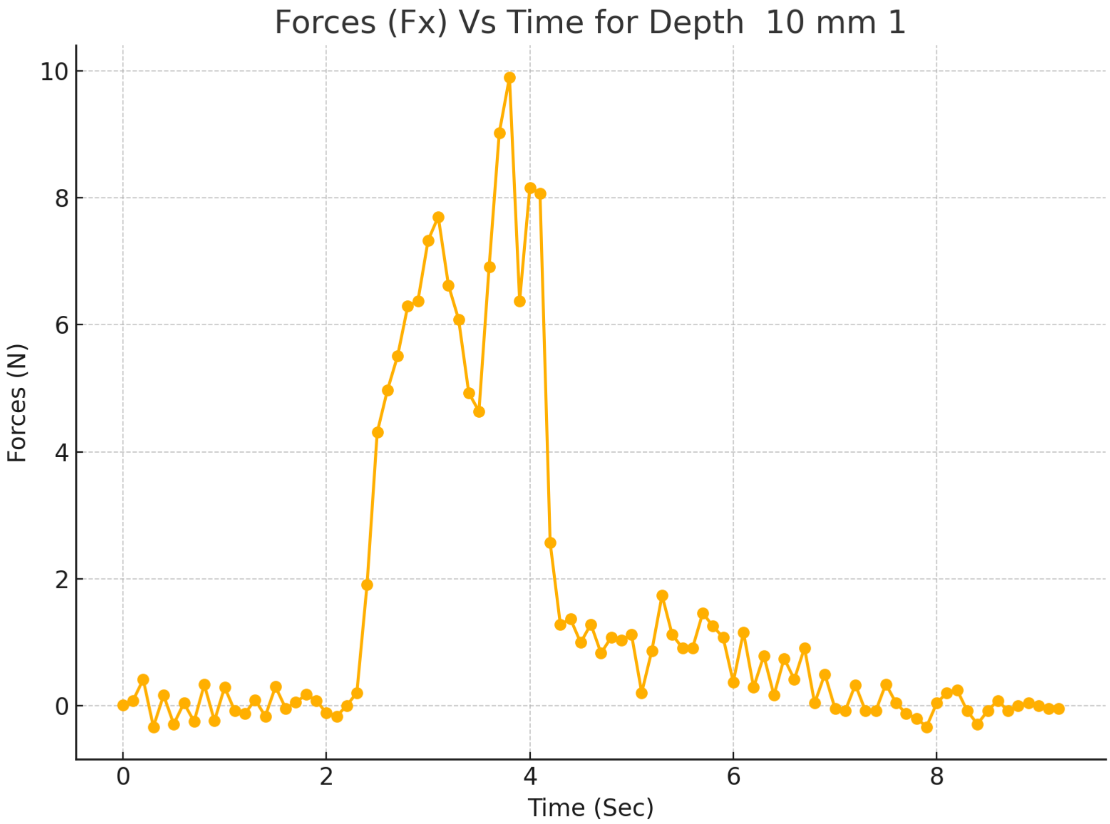


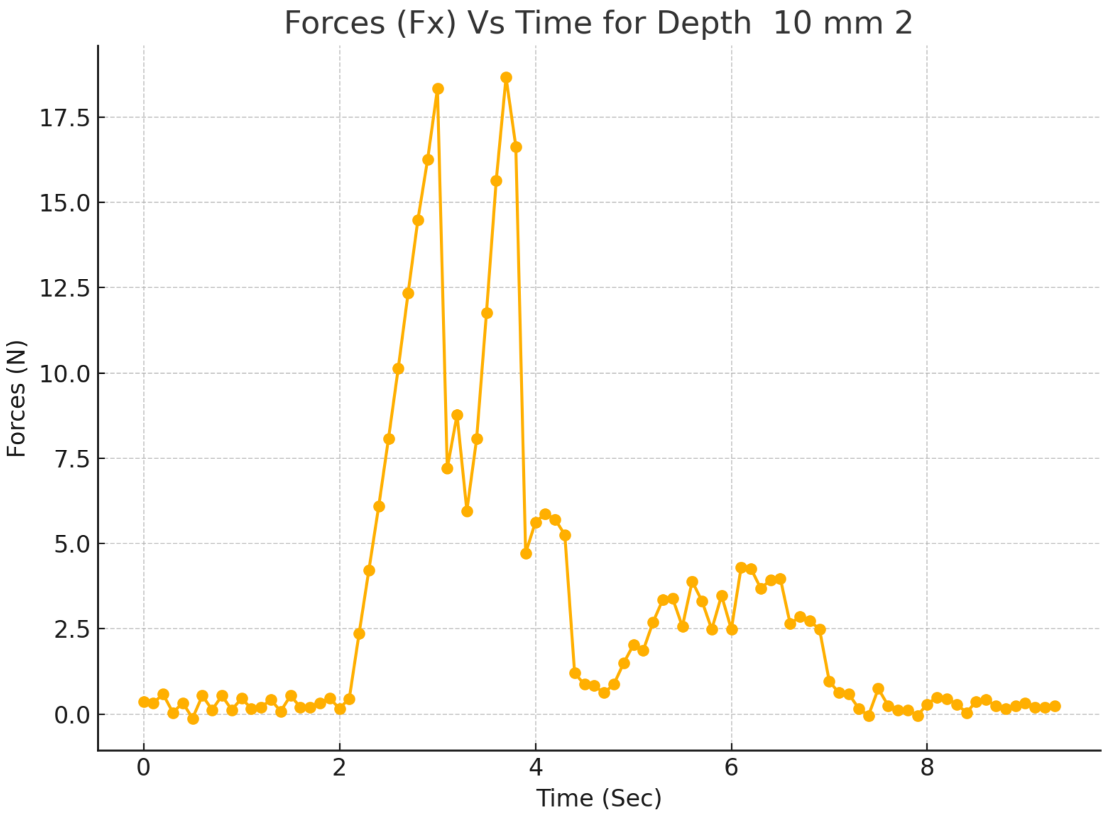
Forces (Fx) Vs Time for Cut 8
Forces (N)
Time (Sec)
0
10
20
30
40
50
60
0
2
4
6
8

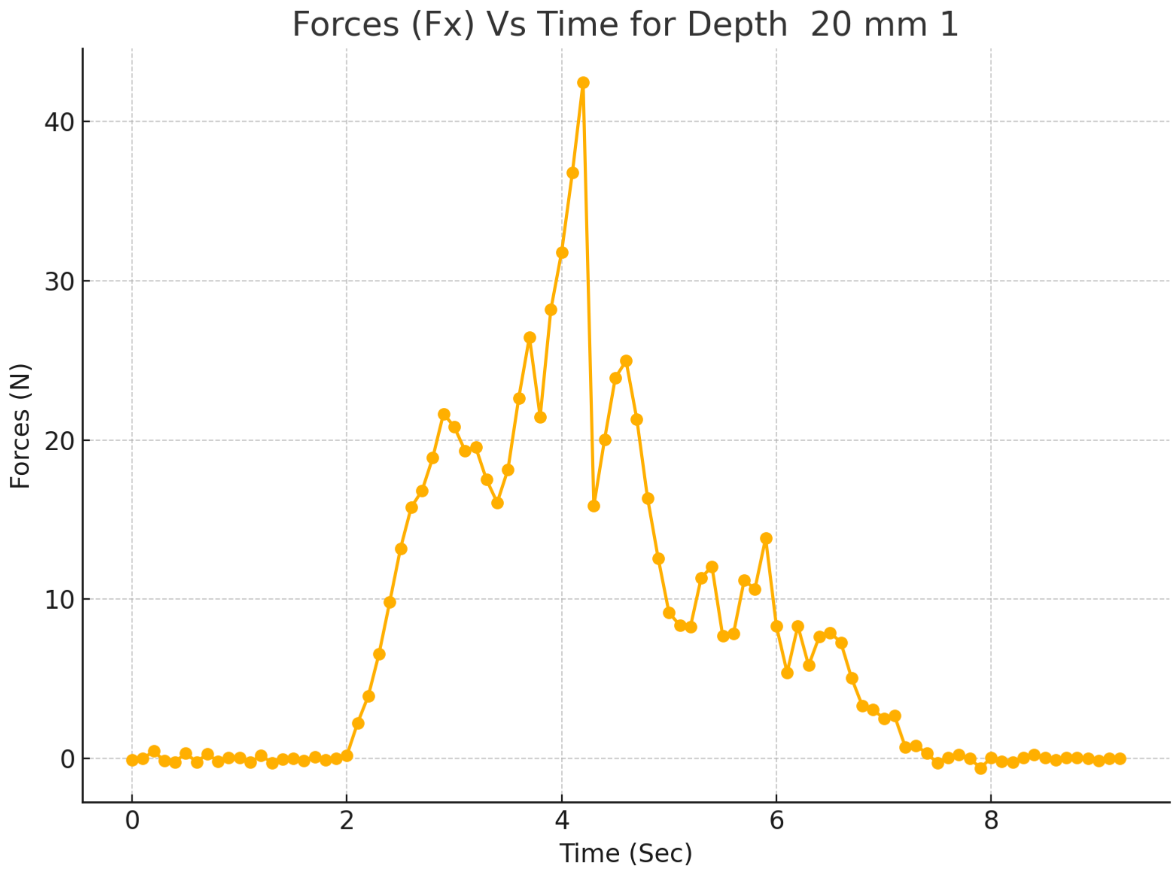


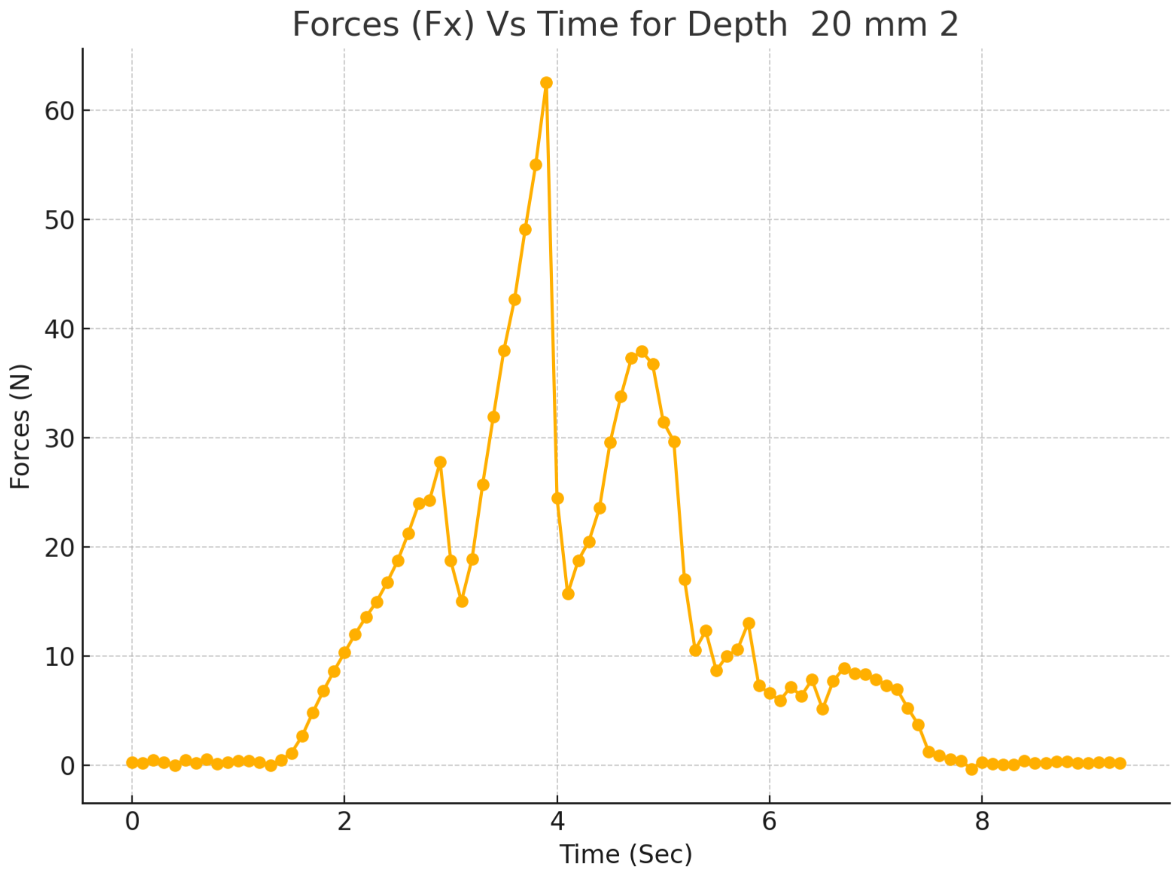
Forces (Fx) Vs Time for Cut 9
Forces (N)
Time (Sec)
0
10
20
30
40
50
60
0
2
4
6
8

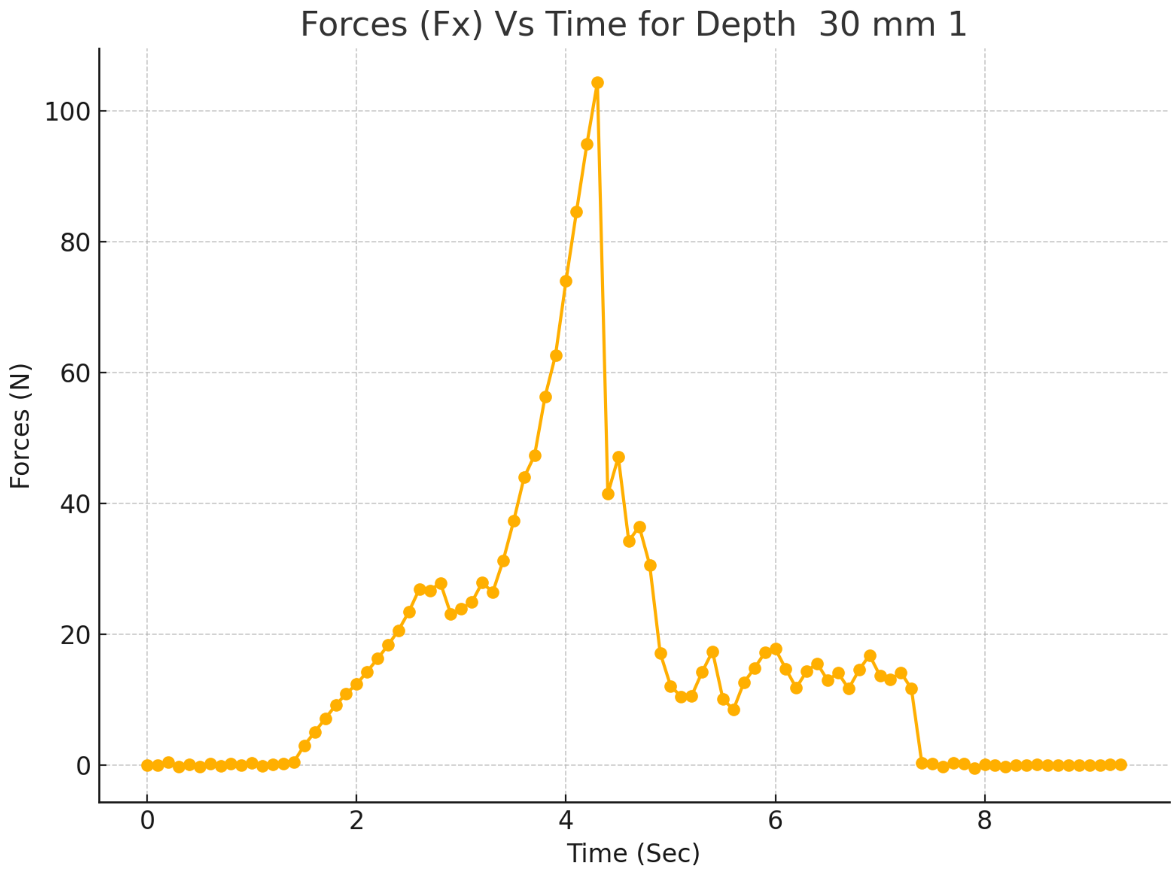
A.1.3. Cutting at different depths

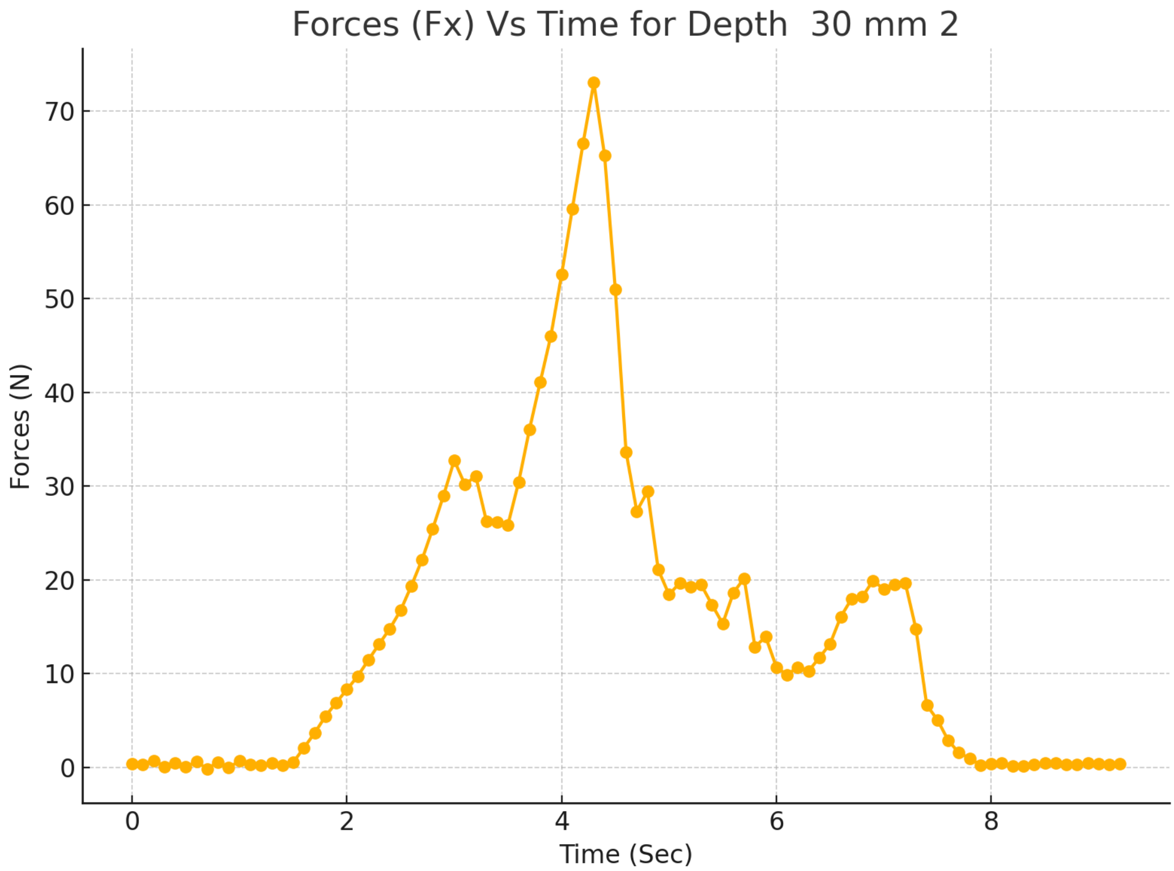





Forces (Fx) Vs Time for Depth 20 mm 1
Forces (N)
Time (Sec)
0
10
20
30
40
0
2
4
6
8


Forces (Fx) Vs Time for Depth 20 mm 2
Forces (N)
Time (Sec)
0
10
20
30
40
50
60
0
2
4
6
8


Forces (Fx) Vs Time for Depth 30 mm 1
Forces (N)
Time (Sec)
0
20
40
60
80
100
0
2
4
6
8

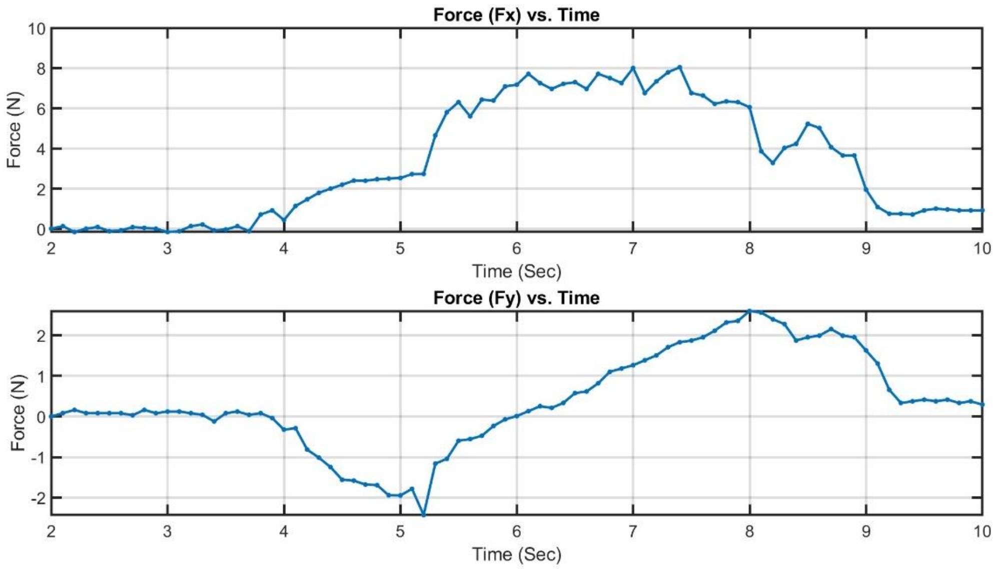

Forces (Fx) Vs Time for Depth 30 mm 2
Forces (N)
Time (Sec)
0
10
20
30
40
50
60
70
0
2
4
6
8

A.2. Chapter 5 data (Sections 5.1 and 5.2)

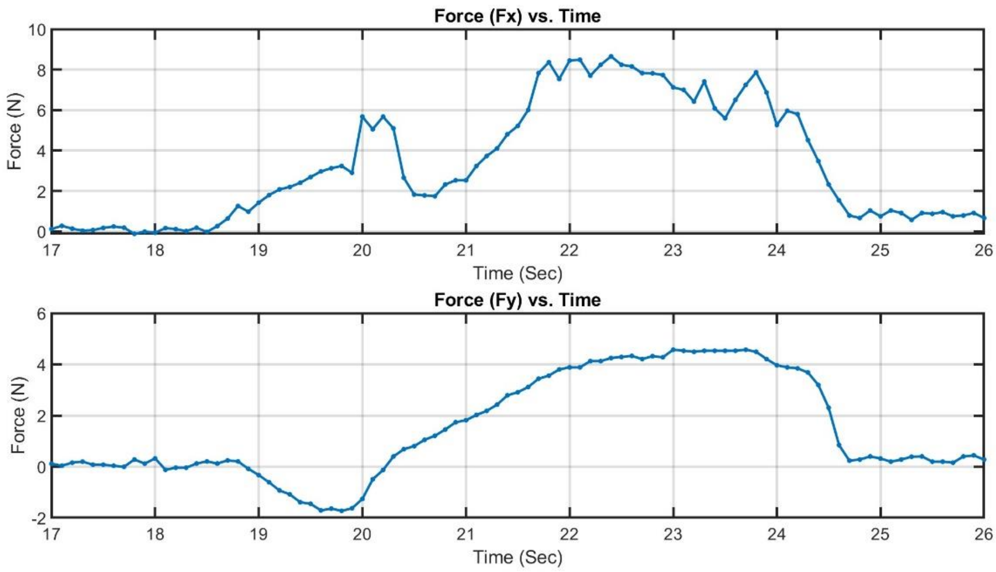
The first three pieces have cuts progressively moving away from the fat/lean interface. The last three pieces have cuts made across the fat layer from one side to the other, near the fat/lean interface.

A.2.1. Piece 1

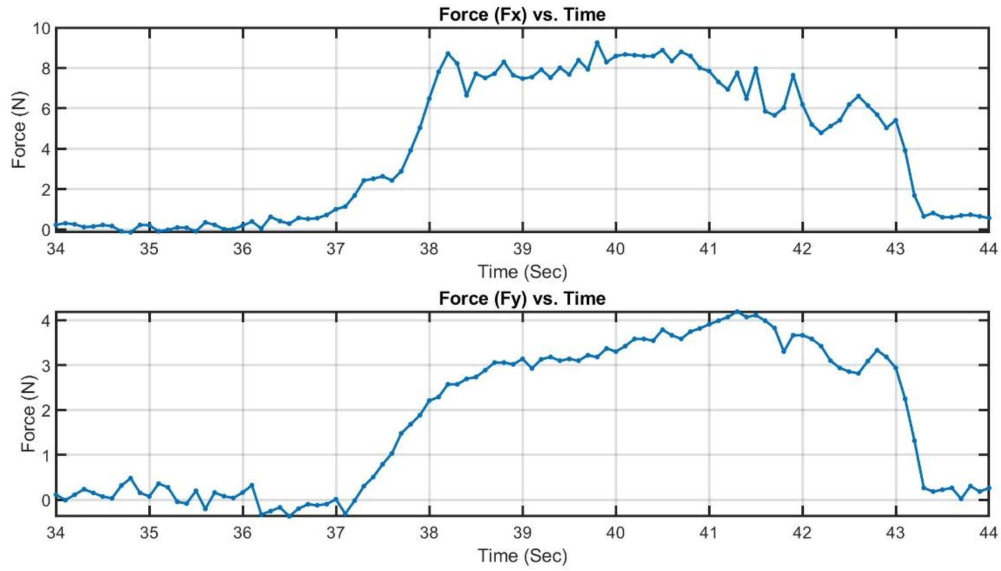
Path 1



Path 2

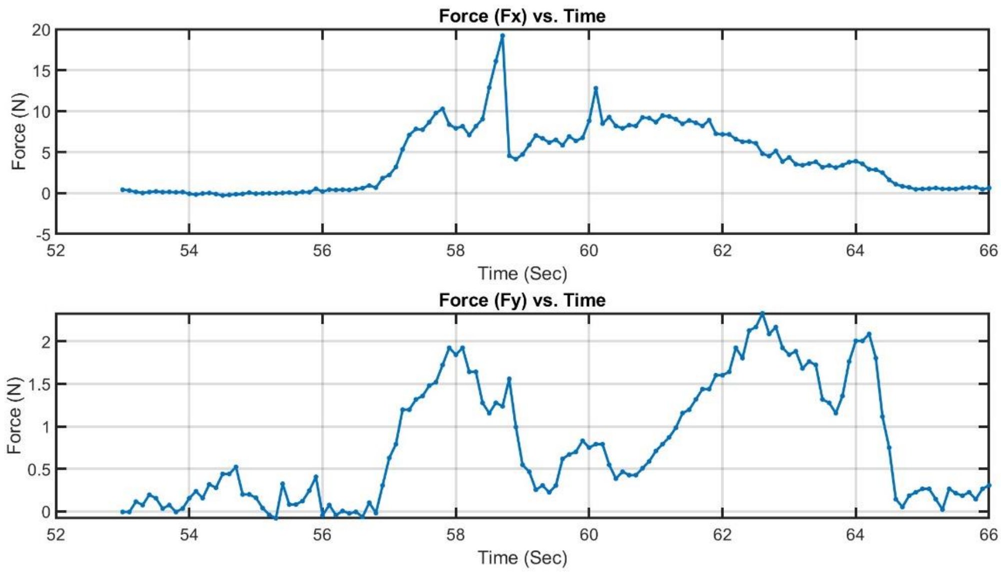


Path 3



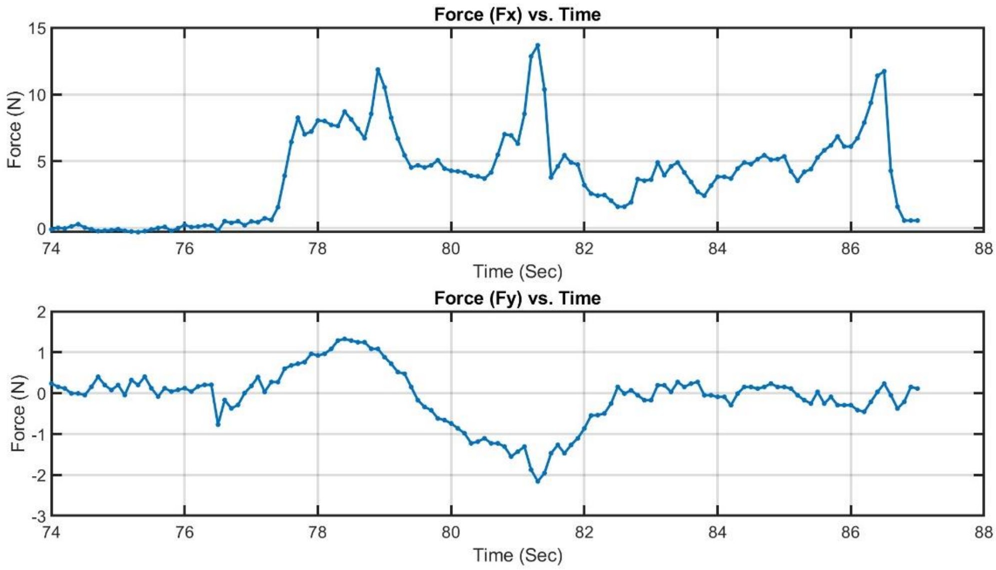
Force (Fx) vs. Time
Force (N)
Time (Sec)
Force (Fy) vs. Time
Force (N)
Time (Sec)

Path 4



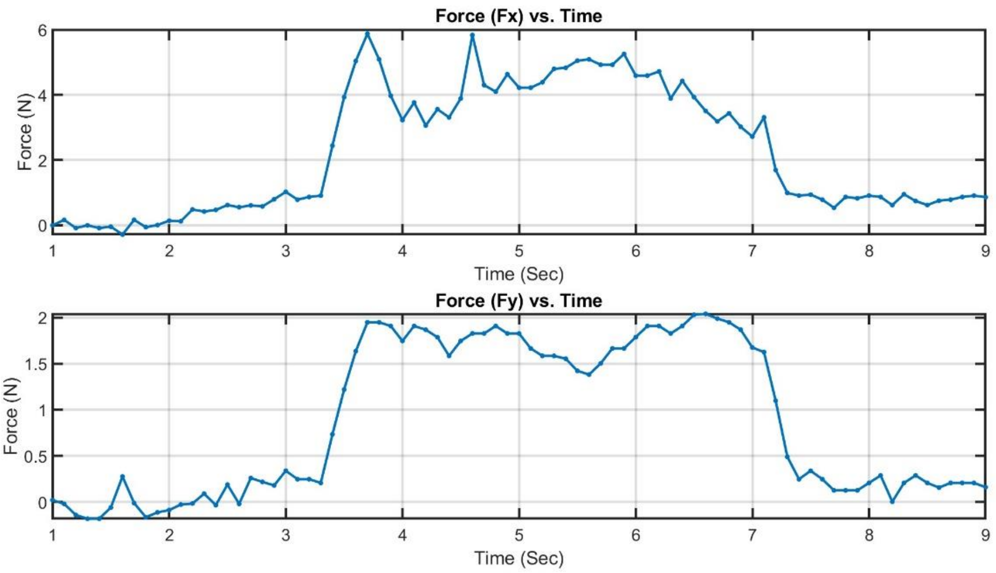
Force (Fx) vs. Time
Force (N)
Time (Sec)
Force (Fy) vs. Time
Force (N)
Time (Sec)

Path 5

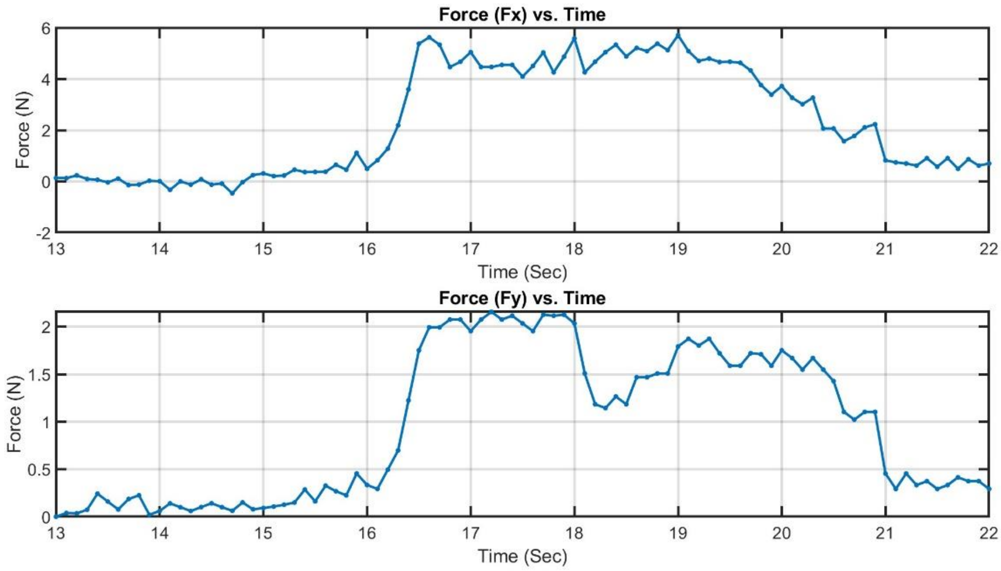


A.2.2. Piece 2

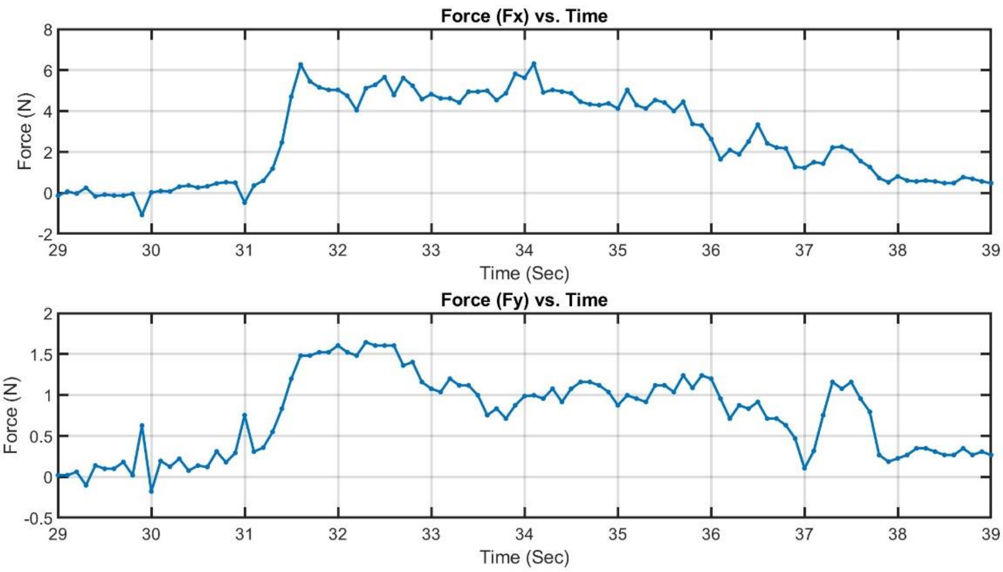
Path 1



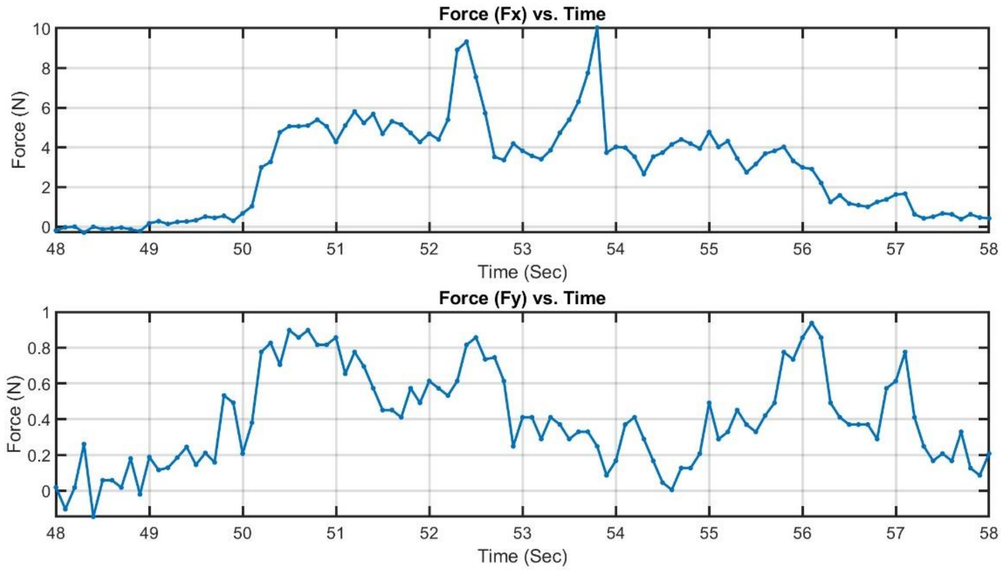
Path 2


Force (Fx) vs. Time
Force (N)
Time (Sec)
Force (Fy) vs. Time
Force (N)
Time (Sec)

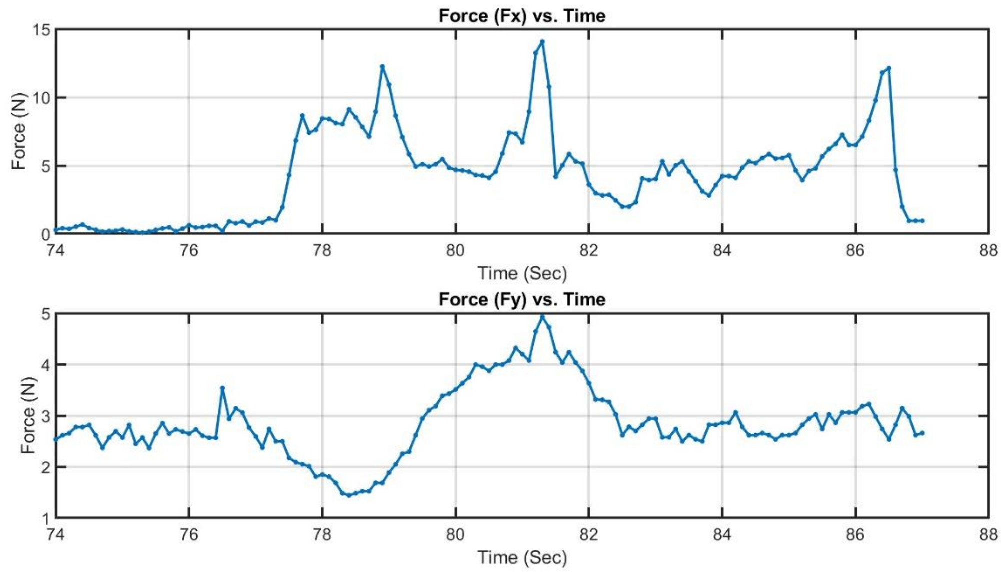
Path 3


Force (Fx) vs. Time
Force (N)
Time (Sec)
Force (Fy) vs. Time
Force (N)
Time (Sec)

Path 4

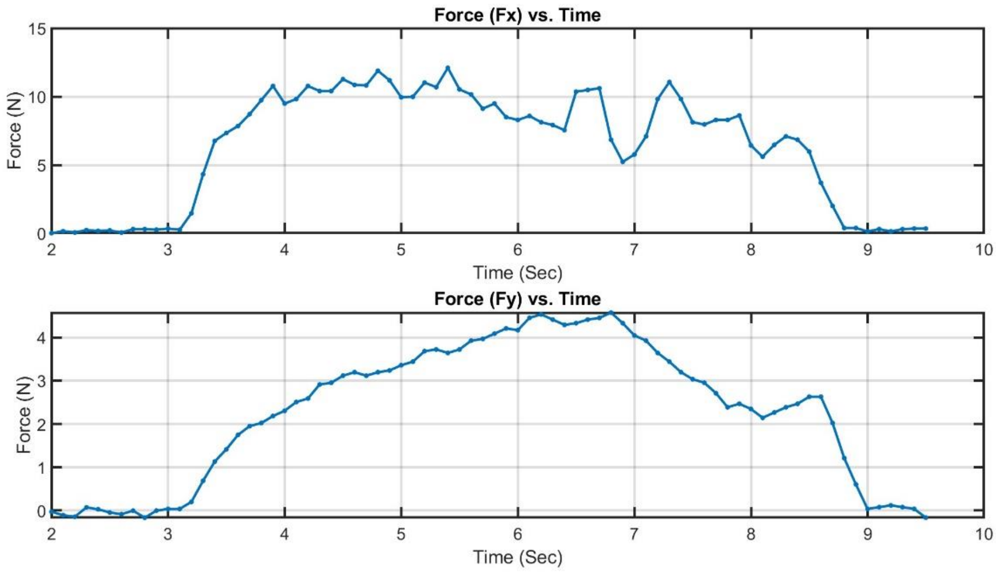

Force (Fx) vs. Time
Force (N)
Time (Sec)
Force (Fy) vs. Time
Force (N)
Time (Sec)

Path 5

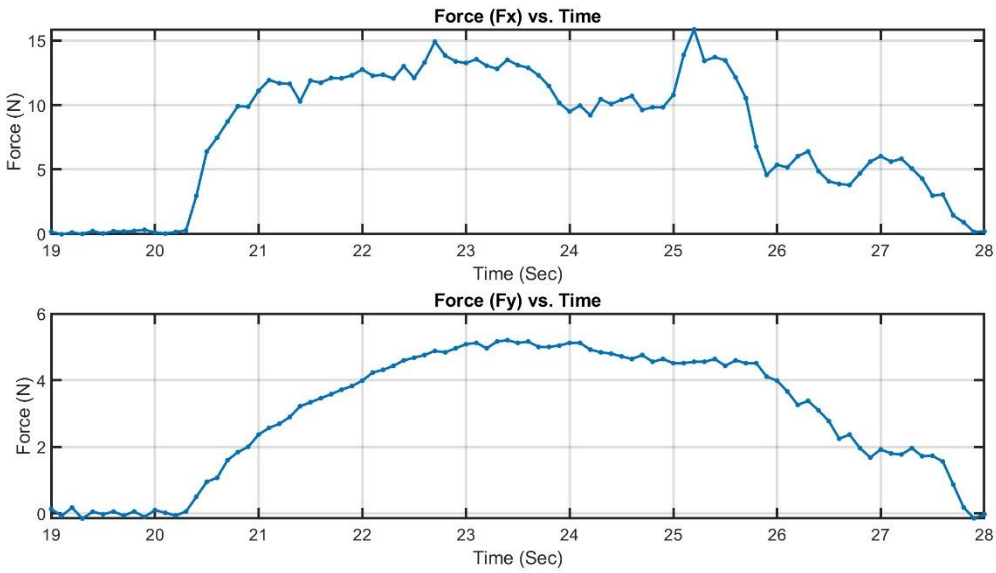

Force (Fx) vs. Time
Force (N)
Time (Sec)
Force (Fy) vs. Time
Force (N)
Time (Sec)

A.2.3. Piece 3

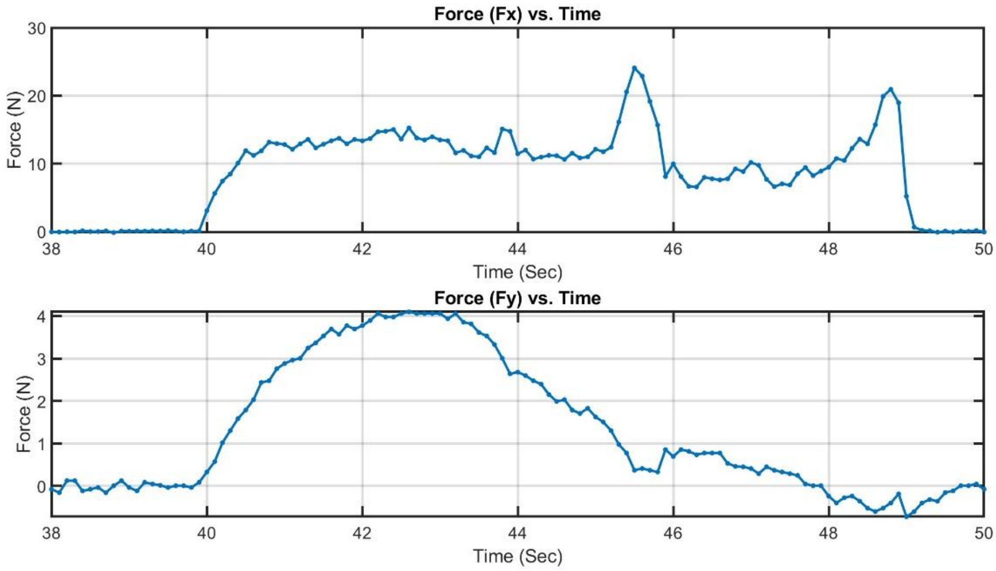
Path 1



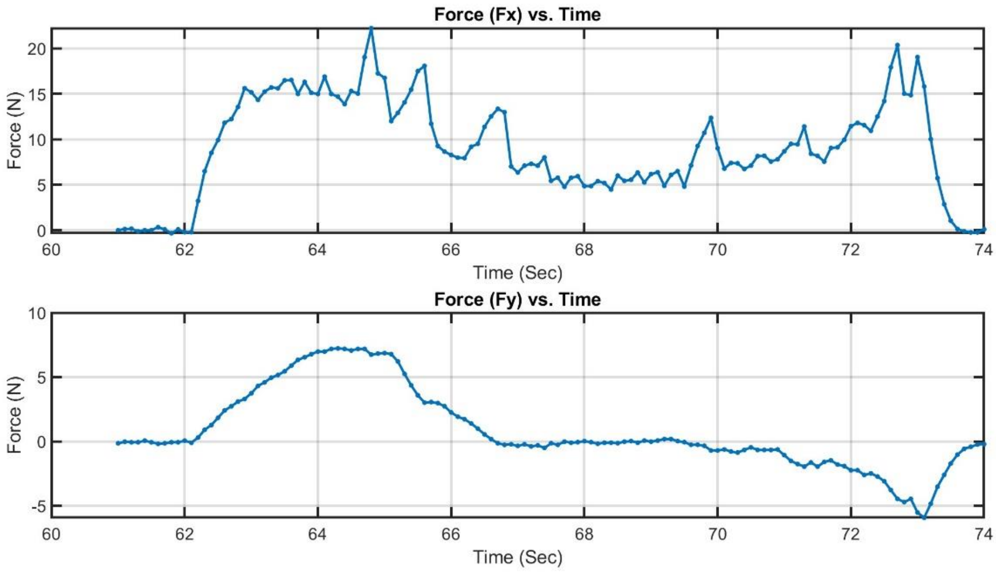
Path 2



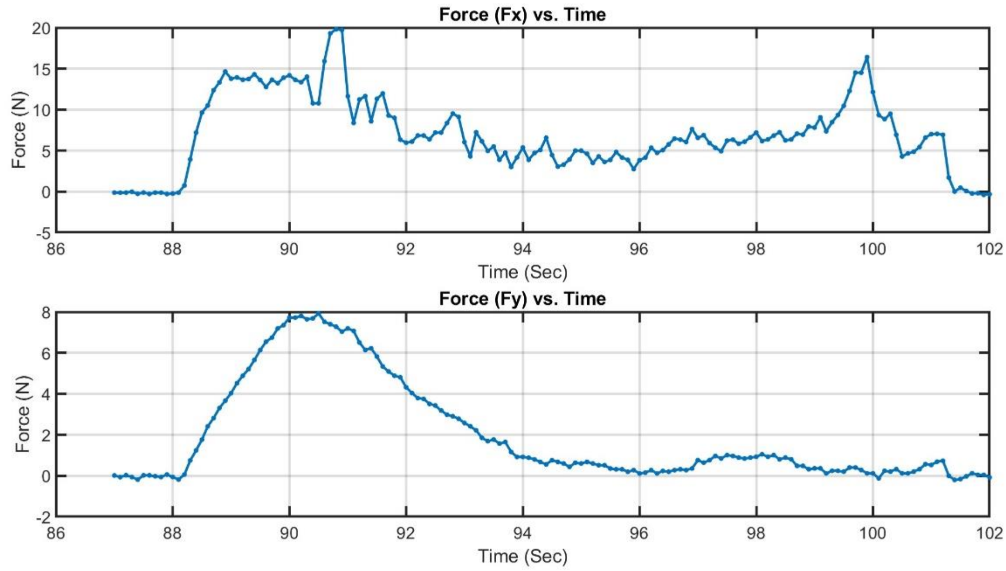
Path 3


Force (Fx) vs. Time
Force (N)
Time (Sec)
Force (Fy) vs. Time
Force (N)
Time (Sec)

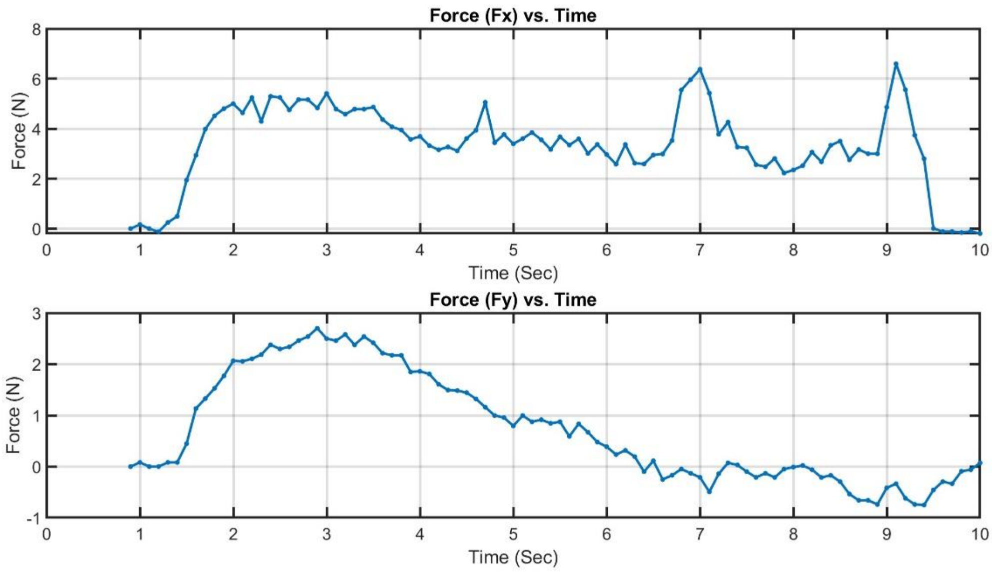
Path 4


Force (Fx) vs. Time
Force (N)
Time (Sec)
Force (Fy) vs. Time
Force (N)
Time (Sec)

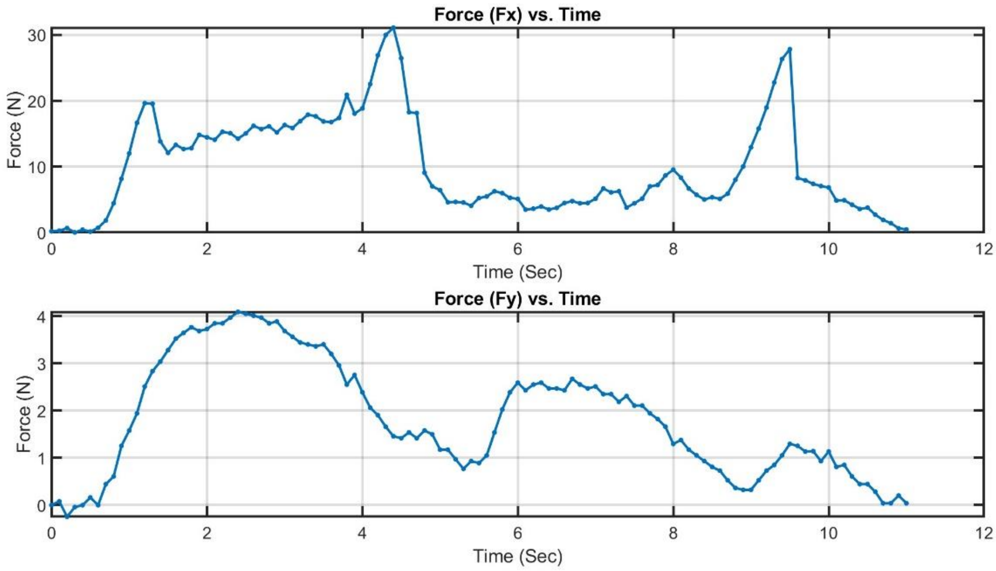
Path 5



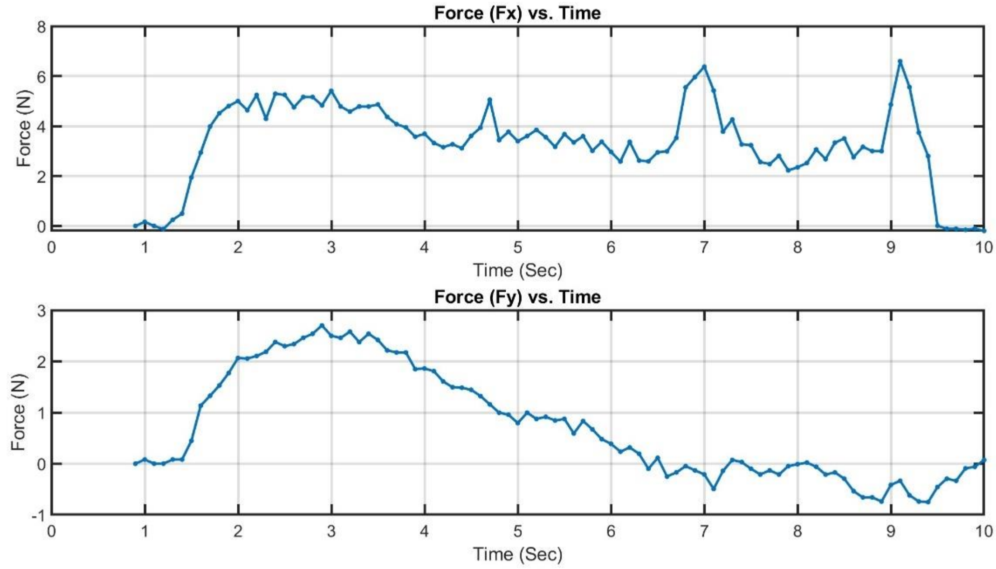
A.2.4. Piece 4



A.2.5. Piece 5



A.2.6. Piece 6



APPENDIX B: MATLAB CODE TO DETECT THE FAT EXISTING CONDITIONS (Section 5.2)

```
% Set formatting variables
lineWidth = 3;
markerSize = 20;
fontSize = 20;
axisLineWidth = 3;
axisFontSize = 20;

% Load the data
data_fx = readtable('Trim1X.xlsx');         % Excel sheets name
data_fy = readtable('Trim1Y.xlsx');

% Apply simple moving average for filtering the data from noise
window_size = 10;    %The window size of the filter
data_fx.Fx_smooth = movmean(data_fx.Fx, window_size);
data_fy.Fy_smooth = movmean(data_fy.Fy, window_size);

% Compute the derivative of Fx with respect to time
data_fx.dFx_dt = [NaN; diff(data_fx.Fx_smooth) ./ diff(data_fx.Timer)];
data_fx.dFx_dt_smooth = movmean(data_fx.dFx_dt, window_size);

% Initialize buffers for live data simulation
buffer_size = 50;  % Size of the buffer to hold recent data

% Initialize buffers
buffer_fx = NaN(buffer_size, 1);
buffer_fy = NaN(buffer_size, 1);
buffer_time = NaN(buffer_size, 1);

% Variable to store the index where the condition is met
condition_met_index = NaN;

% Simulate live data input, This loop receives the data points one by one, adds
them to the buffer, and starts looking for the predetermined cutting conditions.
for t = 1:height(data_fx)
    % Simulate new data point
    new_time = data_fx.Timer(t);
    new_fx = data_fx.Fx(t);
    new_fy = data_fy.Fy(t);

    % Process the new data point
    condition_met = process_new_data(new_time, new_fx, new_fy, window_size,
data_fx, t);     %This function looks for the cutting conditons

    % Pause to simulate real-time data acquisition
    pause(0.01);  % Adjust based on your data acquisition rate

    % Exit loop if the condition is met
    if condition_met
        condition_met_index = t;
        break;
    end
end
```

```
% If a condition is met, plot the results
if ~isnan(condition_met_index)
    % Extract relevant information
    relevant_indices = max(1, condition_met_index-
buffer_size+1):condition_met_index;
    relevant_fx = data_fx.Fx(relevant_indices);
    relevant_fy = data_fy.Fy(relevant_indices);
    relevant_time = data_fx.Timer(relevant_indices);
    relevant_dFx_dt_smooth = data_fx.dFx_dt_smooth(relevant_indices);

    % Plot the smoothed data
    figure;
    subplot(3, 1, 1);
    plot(data_fx.Timer, data_fx.Fx, '-b', 'LineWidth', lineWidth);
    hold on;
    plot(data_fx.Timer, data_fx.Fx_smooth, '--r', 'LineWidth', lineWidth);
    xlabel('Time (Sec)', 'FontSize', fontSize);
    ylabel('Force (N)', 'FontSize', fontSize);
    title('Force (Fx) vs. Time', 'FontSize', fontSize);
    legend('Original Fx', 'Smoothed Fx');
    set(gca, 'LineWidth', axisLineWidth, 'FontSize', axisFontSize);
    grid on;

    subplot(3, 1, 2);
    plot(data_fy.Timer, data_fy.Fy, '-b', 'LineWidth', lineWidth);
    hold on;
    plot(data_fy.Timer, data_fy.Fy_smooth, '--r', 'LineWidth', lineWidth);
    xlabel('Time (Sec)', 'FontSize', fontSize);
    ylabel('Force (N)', 'FontSize', fontSize);
    title('Force (Fy) vs. Time', 'FontSize', fontSize);
    legend('Original Fy', 'Smoothed Fy');
    set(gca, 'LineWidth', axisLineWidth, 'FontSize', axisFontSize);
    grid on;

    subplot(3, 1, 3);
    plot(data_fx.Timer, data_fx.dFx_dt_smooth, 'LineWidth', lineWidth);
    hold on;
    plot(data_fx.Timer(condition_met_index),
data_fx.dFx_dt_smooth(condition_met_index), 'ro', 'MarkerSize', markerSize);
    xlabel('Time (Sec)', 'FontSize', fontSize);
    ylabel('dFx/dt (N/s)', 'FontSize', fontSize);
    title('Smoothed Derivative of Force (Fx) vs. Time', 'FontSize', fontSize);
    legend('Smoothed dFx/dt', 'Point of Interest');
    set(gca, 'LineWidth', axisLineWidth, 'FontSize', axisFontSize);
    grid on;

    % Plot the peaks in Fy and points of interest in dFx/dt
    figure;
    subplot(2, 1, 1);
    plot(data_fy.Timer, data_fy.Fy_smooth, 'LineWidth', lineWidth);
    hold on;
    plot(data_fy.Timer(condition_met_index),
data_fy.Fy_smooth(condition_met_index), 'ro', 'MarkerSize', markerSize);
    xlabel('Time (Sec)', 'FontSize', fontSize);
    ylabel('Force (N)', 'FontSize', fontSize);
    title('Forces on the side of the knife (Fy)', 'FontSize', fontSize);
    legend('Smoothed Fy', 'Point of Interest');
    set(gca, 'LineWidth', axisLineWidth, 'FontSize', axisFontSize);
    grid on;
```

```
    subplot(2, 1, 2);
    plot(data_fx.Timer, data_fx.dFx_dt_smooth, 'LineWidth', lineWidth);
    hold on;
    plot(data_fx.Timer(condition_met_index),
data_fx.dFx_dt_smooth(condition_met_index), 'ro', 'MarkerSize', markerSize);
    xlabel('Time (Sec)', 'FontSize', fontSize);
    ylabel('Rate of change of force (N/s)', 'FontSize', fontSize);
    title('First derivative of Fx', 'FontSize', fontSize);
    legend('Smoothed dFx/dt', 'Point of Interest');
    set(gca, 'LineWidth', axisLineWidth, 'FontSize', axisFontSize);
    grid on;
end

% Function to process new data point
function condition_met = process_new_data(new_time, new_fx, new_fy, window_size,
data_fx, current_index)
    persistent buffer_fx buffer_fy buffer_time buffer_size negative_duration
start_time peak_detected

    if isempty(buffer_fx)
        buffer_size = 50;
        buffer_fx = NaN(buffer_size, 1);
        buffer_fy = NaN(buffer_size, 1);
        buffer_time = NaN(buffer_size, 1);
        negative_duration = 0;
        start_time = NaN;
        peak_detected = false;
    end

    % Update buffers with new data
    buffer_time = [buffer_time(2:end); new_time];
    buffer_fx = [buffer_fx(2:end); new_fx];
    buffer_fy = [buffer_fy(2:end); new_fy];

    % Apply moving average for smoothing
    smoothed_fx = movmean(buffer_fx, window_size);
    smoothed_fy = movmean(buffer_fy, window_size);

    % Compute the derivative of Fx
    dFx_dt = [NaN; diff(smoothed_fx) ./ diff(buffer_time)];

    % Apply smoothing to the derivative
    smoothed_dFx_dt = movmean(dFx_dt, window_size);

    % Store the smoothed derivative in the original data table
    data_fx.dFx_dt_smooth(current_index) = smoothed_dFx_dt(end);

    % Detect peaks in Fy
    [~, peak_indices] = findpeaks(smoothed_fy);

    % Track duration where dFx/dt is negative
    if smoothed_dFx_dt(end) < 0
        if isnan(start_time)
            start_time = buffer_time(end);
        end
        negative_duration = buffer_time(end) - start_time;
    else
        start_time = NaN;
```

```
        negative_duration = 0;
    end

    % Check if there is a peak in Fy during the negative duration
    if negative_duration >= 0.5
        % Check if any peak is detected during this period
        for i = 1:length(peak_indices)
            if buffer_time(peak_indices(i)) >= start_time &&
buffer_time(peak_indices(i)) <= buffer_time(end)
                peak_detected = true;
                peak_time = buffer_time(peak_indices(i));
                break;
            end
        end
    else
        peak_detected = false;
    end

    % If both conditions are met, display the result and return true
    if peak_detected
        disp(['Conditions met at time: ', num2str(peak_time)]);
        disp(['Fx: ', num2str(buffer_fx(peak_indices(i))), ...
              ', Fy: ', num2str(buffer_fy(peak_indices(i))), ...
              ', dFx/dt: ', num2str(smoothed_dFx_dt(peak_indices(i)))]);
        condition_met = true;
    else
        condition_met = false;
    end
end
```

APPENDIX C: FORCE SENSOR SETUP AND CALIBRATION

The section explores one specific force sensor, ABB 165. The way it is set up and appropriately calibrated to provide accurate force readings. Then, it views the general basic theory of work and the different configurations behind strain gauge-based force sensors.

C.2 Sensor set up

C.2.1 Hardware connection

The ABB force sensor comes with the following components (ABB, 2015):

i. Force sensor plate
ii. Voltage measurement box
iii. Control cable
iv. Sensor cable
v. Adapter plate

Figure 60: ABB force sensor 165 hardware components (ABB, 2015)

The sensor is connected to the manipulator using the adapter plate after correctly orienting the sensor's coordinates relative to the manipulator coordinates by lining up the axes marks on both sides. The correct orientation of the sensor to be connected to the robot arm can be shown in Figure 61.

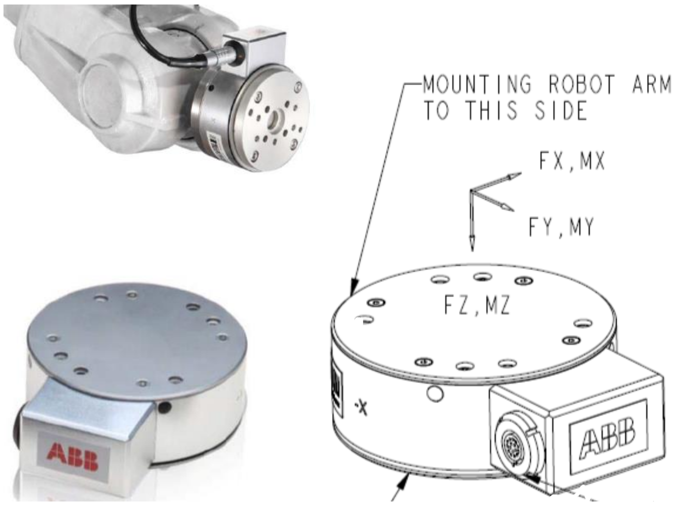


Figure 61: ABB force sensor 165 alignment lines (ABB, 2015)

After that, the sensor is interfaced with the IRC5 controller using the voltage measurement board. The final setup is illustrated in **Figure 62**.

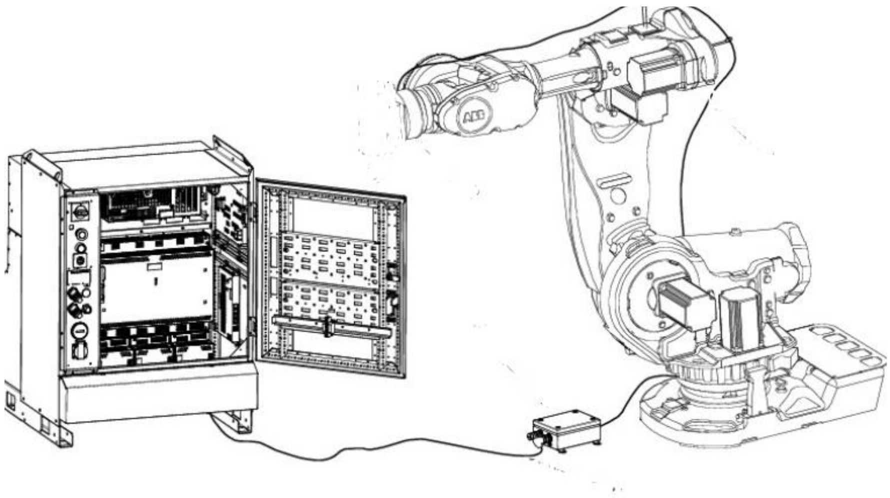


Figure 62: ABB force control connections (ABB, 2015)

C.2.2 Software calibration

For accurate readings, the zero offsets of the sensor will need to be calibrated to remove the noises that could interfere with the data. The attached software allows the user to calibrate the sensor readings by applying the following instructions:

- Set up gravity compensation.
- Set up sensor offset calibration.
- Define the weights attached to the sensor, such as the weight of the cutting tool.

After calibration, the sensor will be tested by applying forces in each direction on the attached cutting tool and examining the sensor's values. The expected zero offset readings of the sensor are shown in Figure **63**.

Sunrise Instuments Calibration Report

Address:2nd Floor Building B2 19#Keyuan Xishi Road Nanning Guangxi Province China 530007
Phone:+86 771-389-9499 Fax:+86 771-389-9497
Email:sri@srisensor.com

SRI

Calibration No.	SRi-OR-39308	Cal Date	2018-3-13
Model No.	3HAC048735-001	Serial No.	5984
Technician	Wang	Temp(C)/Hum.(%).	23.0 / 71.0
Customer	ABB	Excitation(V)	5.0026
Description	F660N D104MM LC	Cable Length	
Comments	SHCS M6:13N.m		

Voltage Calibration

Bridge	Capacity	Zero Offset	Nonlinearity	Hysteresis	Output @ Capacity	Sensitivity	Change
	N/Nm	V	%FS	%FS	V	V/EU	%
FX	-660	-0.0139	-0.23	-0.66	-6.8593	1.0393E-02	0.00
FY	660	-0.0139	0.21	0.64	6.8649	1.0401E-02	0.00
FZ	-1980	-0.0149	-0.09	-0.07	-7.1572	3.6148E-03	0.00
MX	-60	-0.0153	-0.17	-0.26	-7.2745	1.2124E-01	0.00
MY	-60	-0.0152	-0.12	-0.10	-6.9928	1.1655E-01	0.00
MZ	60	-0.0176	0.32	0.31	7.6274	1.2712E-01	0.00

Wire Color Codes

FUNCTION	fx/mx	fy/my	fz/mz
+EXC			
+SIG			
-EXC			
-SIG			
Sensor ID			
ID Return			

CONNECTOR,COLOR CODE SEE SPEC SHEET

Reference Load Cell

Manufacturer	Model Type	Model No.	Serial No.	Cal Due Date
SUNRISE	Golden Standard	M3002-2000N	123	18/07/18

Traceable to the National Institute of Metrology China (NIMC)

This calibration folllows the calibration document SRiLAB-BZ-001:2014 which defined in the Sunrise Instruments Lab

The load cell calibration system consists of a 300KN load frame CMT5305 made by SANS Testing Machine Co., Golden reference load cell by Interface. Data acquisition system by National Instruments.

Calibrated by Approved by

Page 1 of 2

Figure 63: ABB force sensor calibration values

APPENDIX D: CUTTING KNIFE DESCRIPTION

This high-end carbon stainless steel boning knife is designed and crafted for the specialized task of boning meats, catering to both professionals and home cooks. The knife features a stiff, curved blade that provides leverage and precision cutting Figure 64.

Figure 64: The cutting used in the experiments

D.1 Key Features:

- High carbon stainless steel
- Ergonomic nylon handle
- Rockwell Hardness: 56-58
- Made in Switzerland
- Lifetime Warranty
- Product code: #138300

D.2 Specifications:

- **Construction:** High carbon stainless steel, Nylon handle
- **Hardness:** Rockwell 56-58
- **Dimensions:** 16 cm
- **Features:** Stiff curved blade
- **Cleaning/Care:** Dishwasher safe, can be sterilised
- **Made in:** Switzerland
- **Warranty:** Lifetime