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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

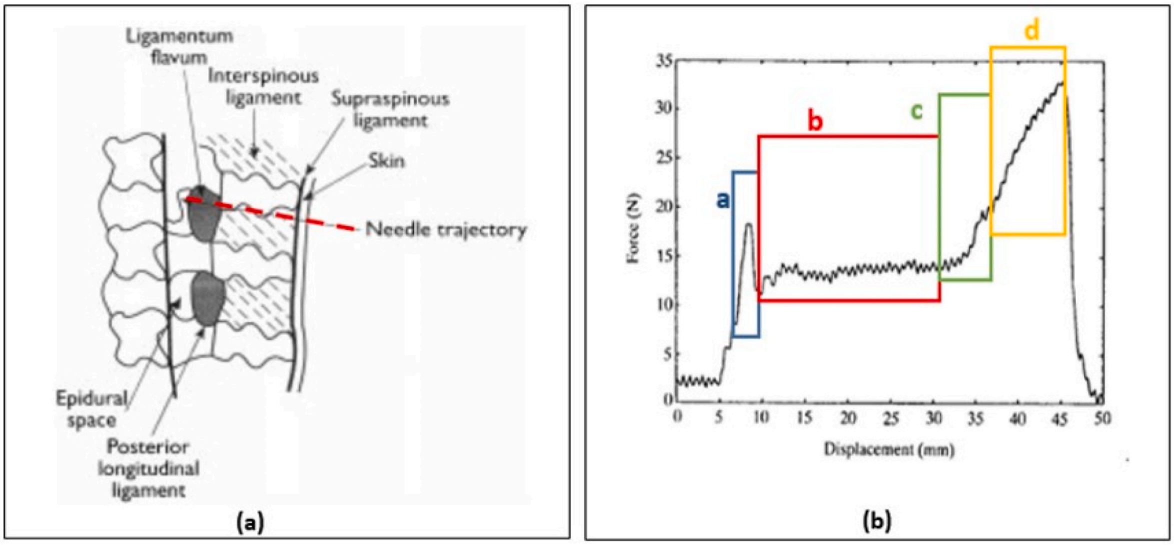


Fig. 1. a) The needle path during the epidural procedure is grouped into types of tissues needle encounters during each stage (Brett et al., 1997), b) The unique force transients during each stage of the epidural procedure (Brett et al., 1997).

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

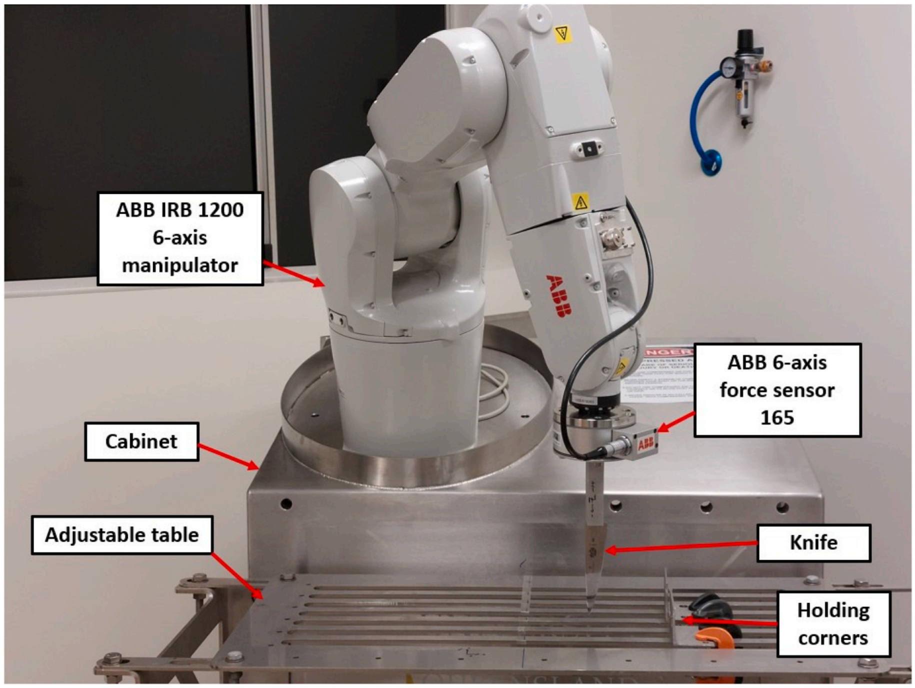


Fig. 2. Test rig setup.

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 inter-muscular 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.

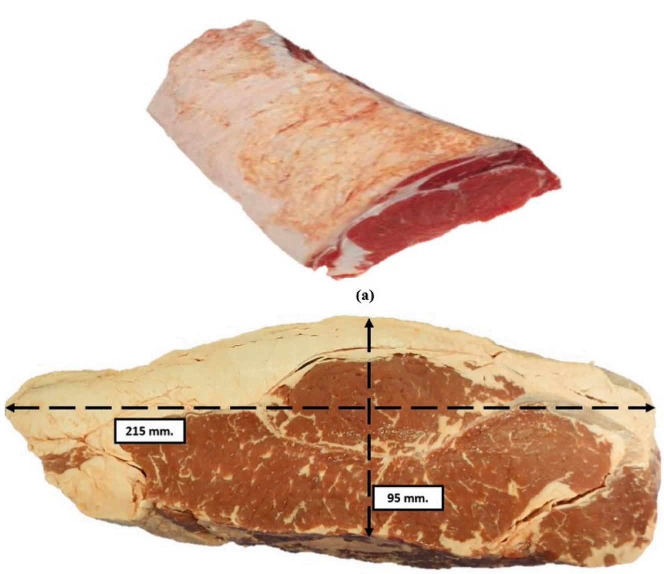


Fig. 3. a) Primary unprocessed striploin product b) Typical measurements of a striploin chop.

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 pre-determined 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.

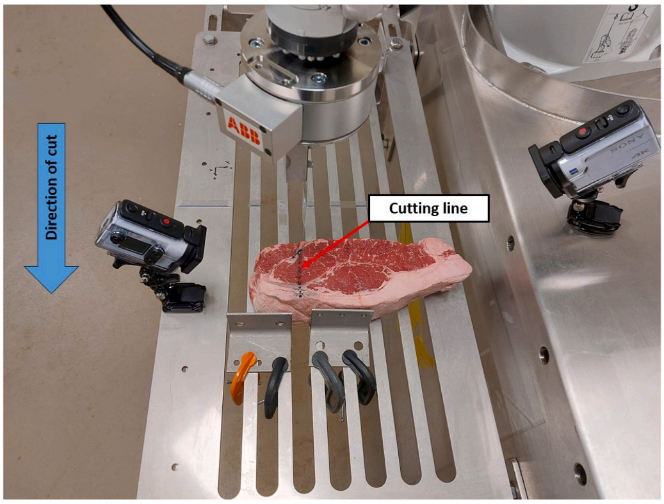


Fig. 4. Experiment setup.

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.

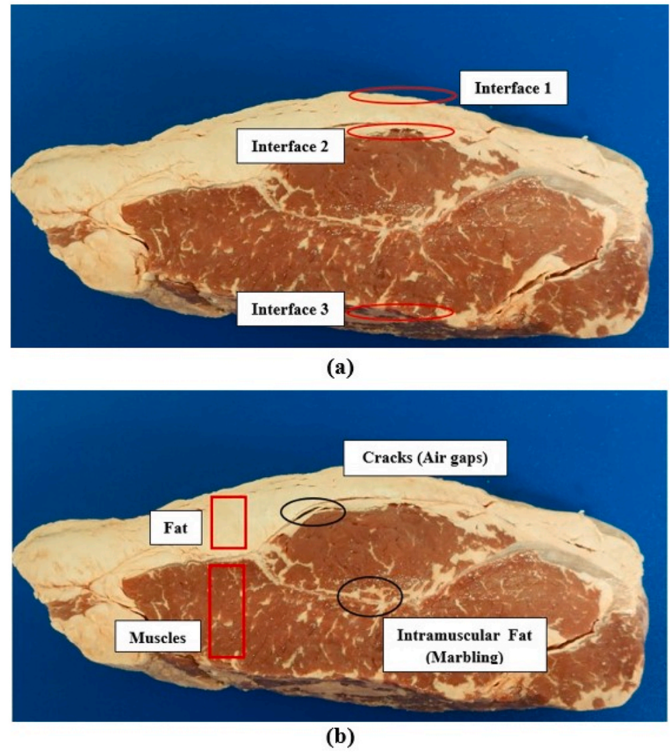


Fig. 5. a) The main interface during the cut, b) Features of fat and muscles.

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*

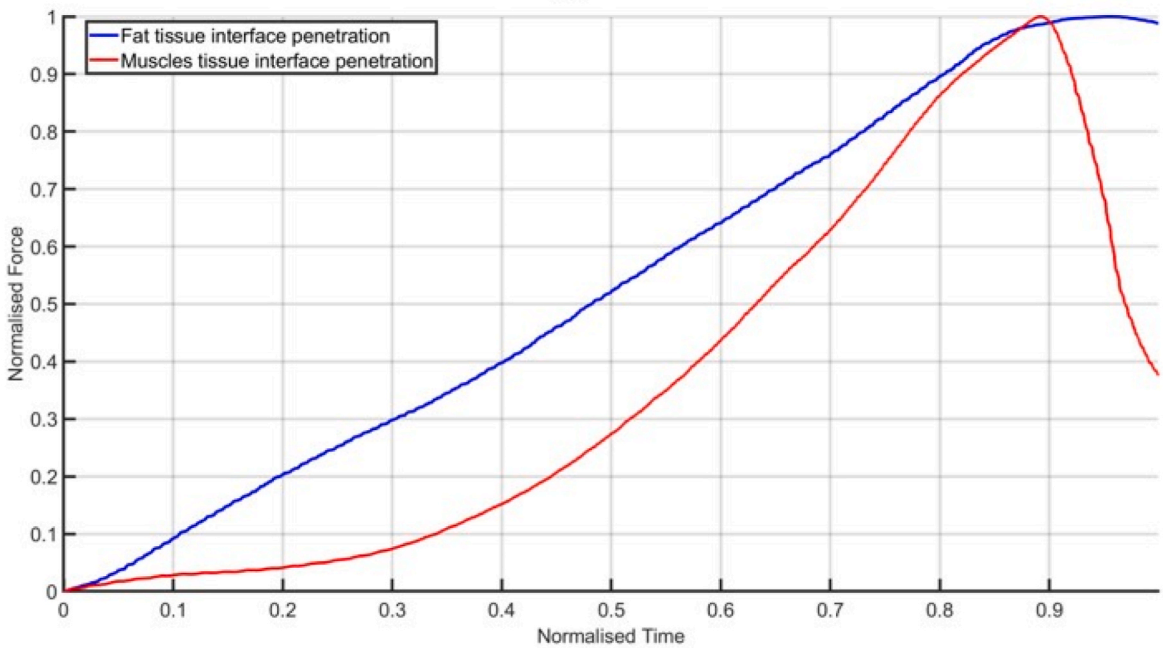
After penetrating the first layer of tissue and the knife enters the sample (regardless of the medium), the force values are sustained at the level needed for cutting the subsequent tissues. The effective forces switched from the puncturing force caused by meat deformation to the cutting and frictional 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

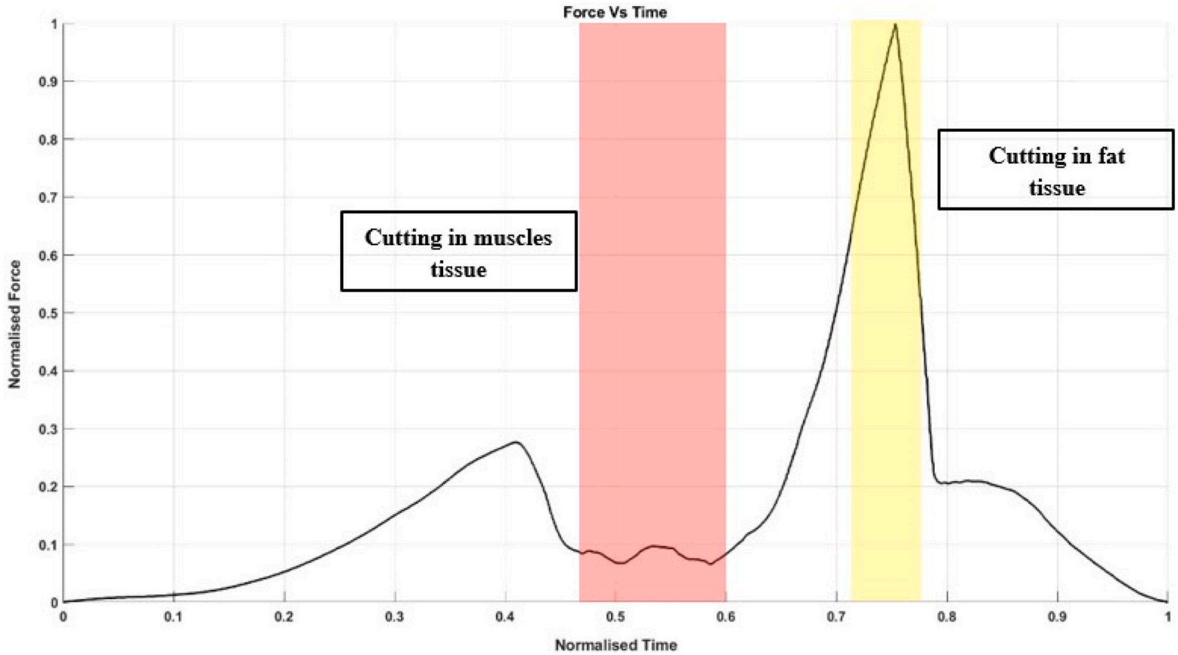


Fig. 7. The average force profile of all the cuts that start from the muscles side.

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

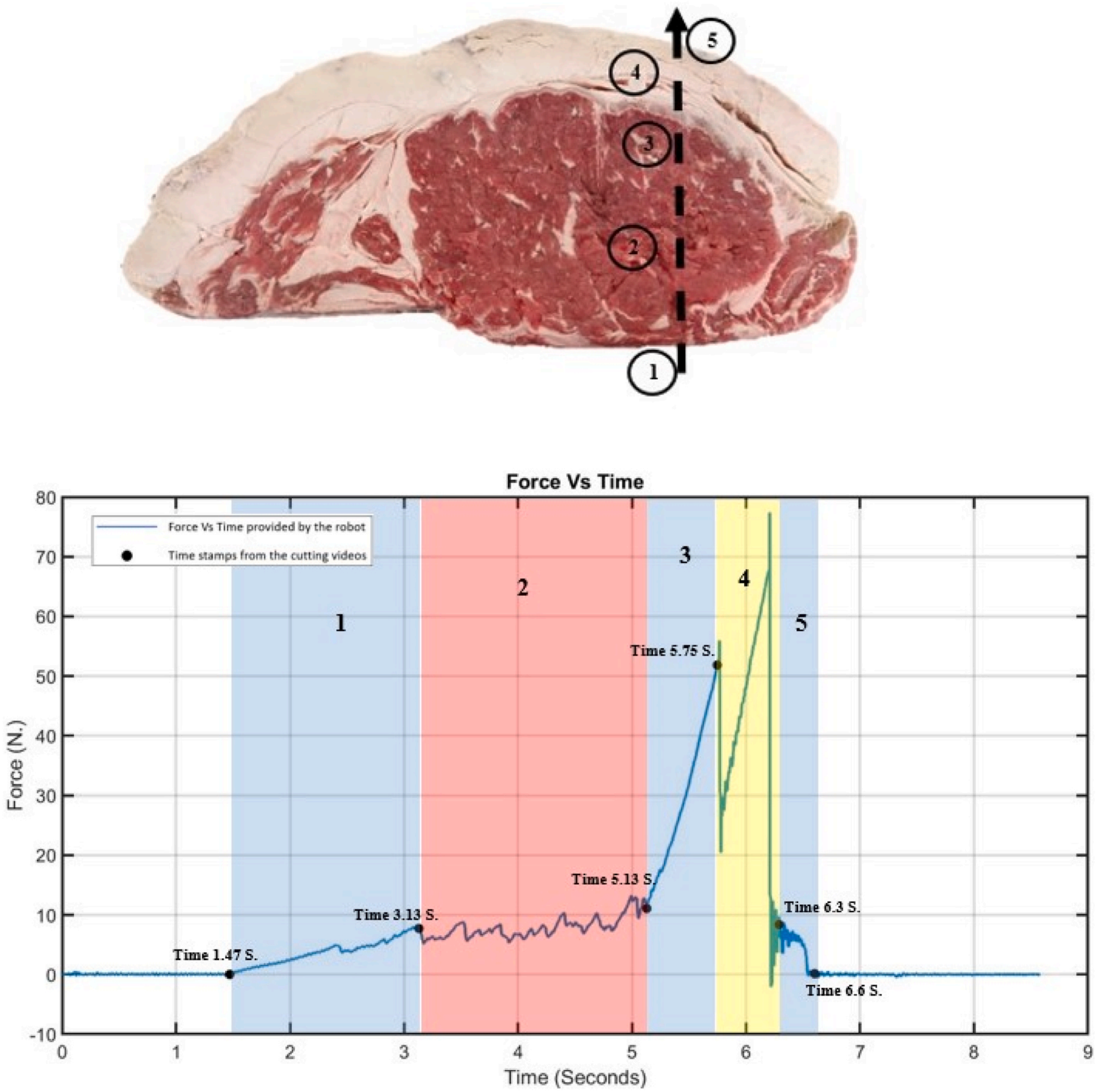


Fig. 8. The stages of cutting through the red meat tissues starting from the muscles side.

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

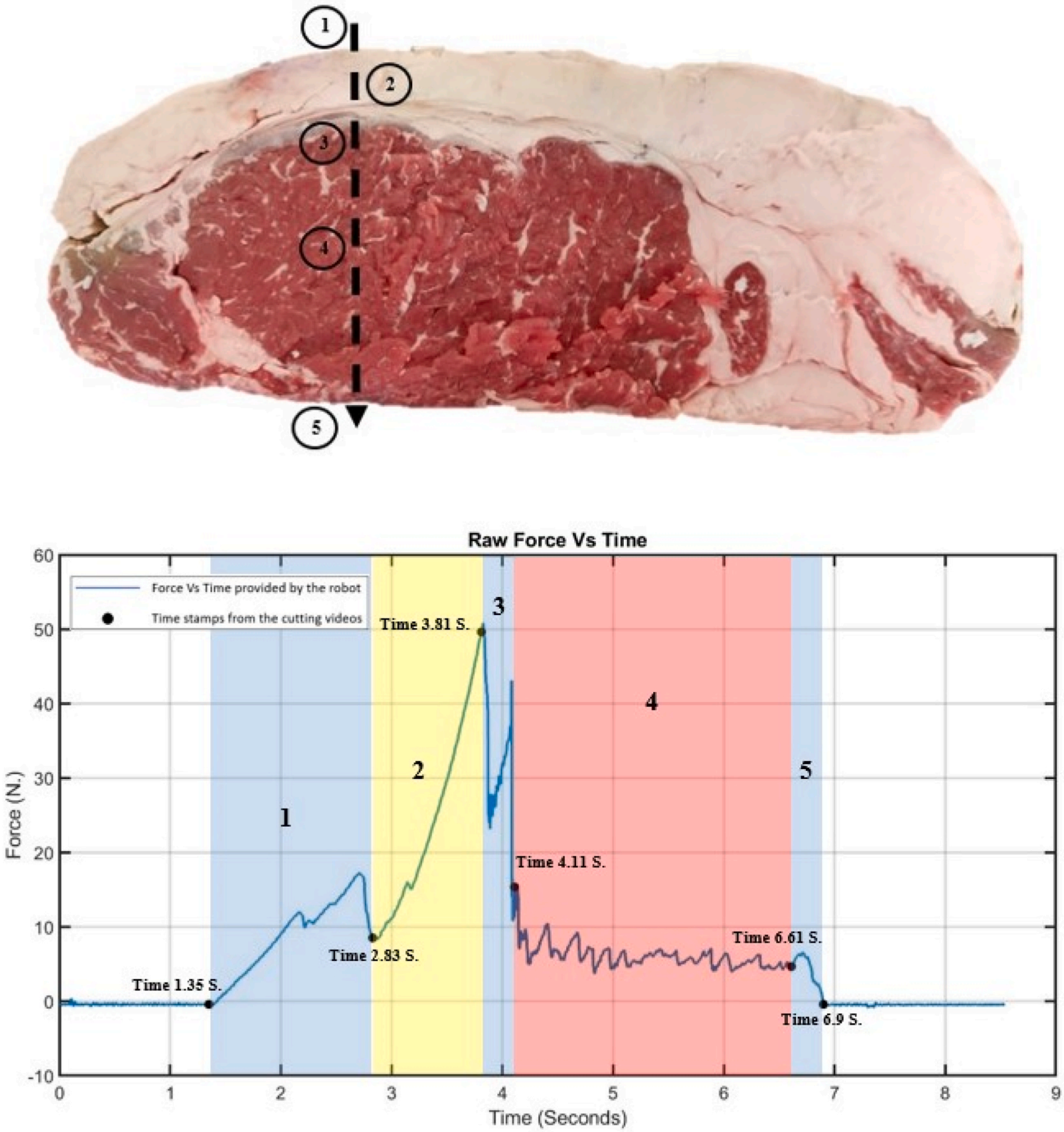


Fig. 9. The stages of cutting through the red meat tissues starting from the fat layer side.

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

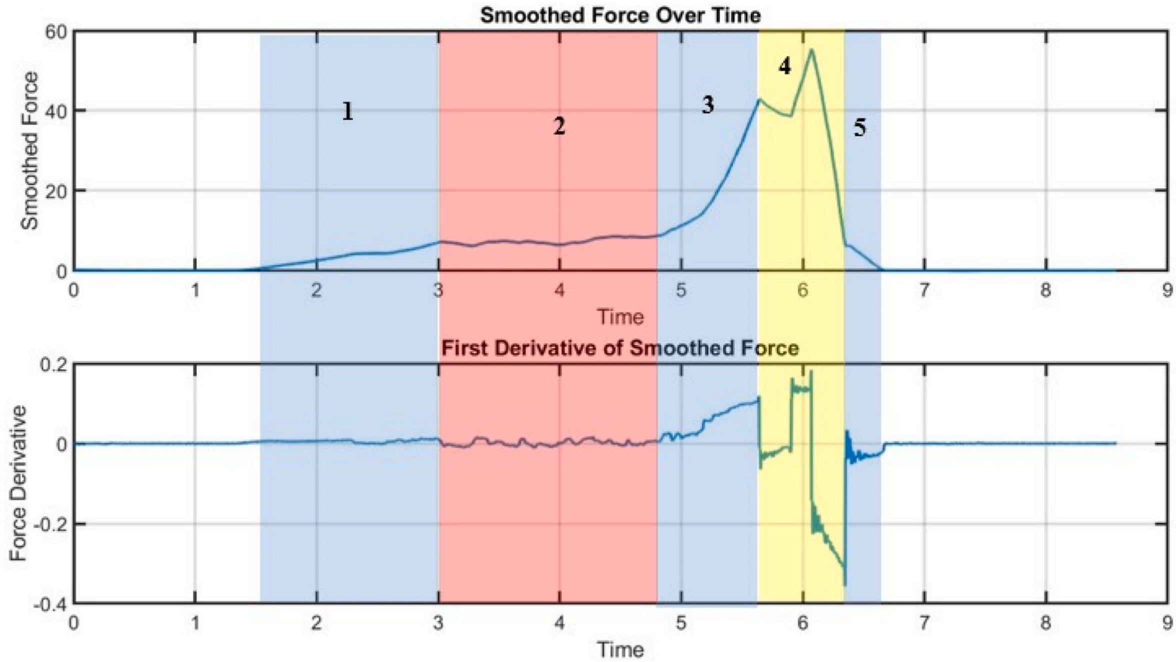


Fig. 10. Identifying tissue interfaces during cutting using gradient plot.

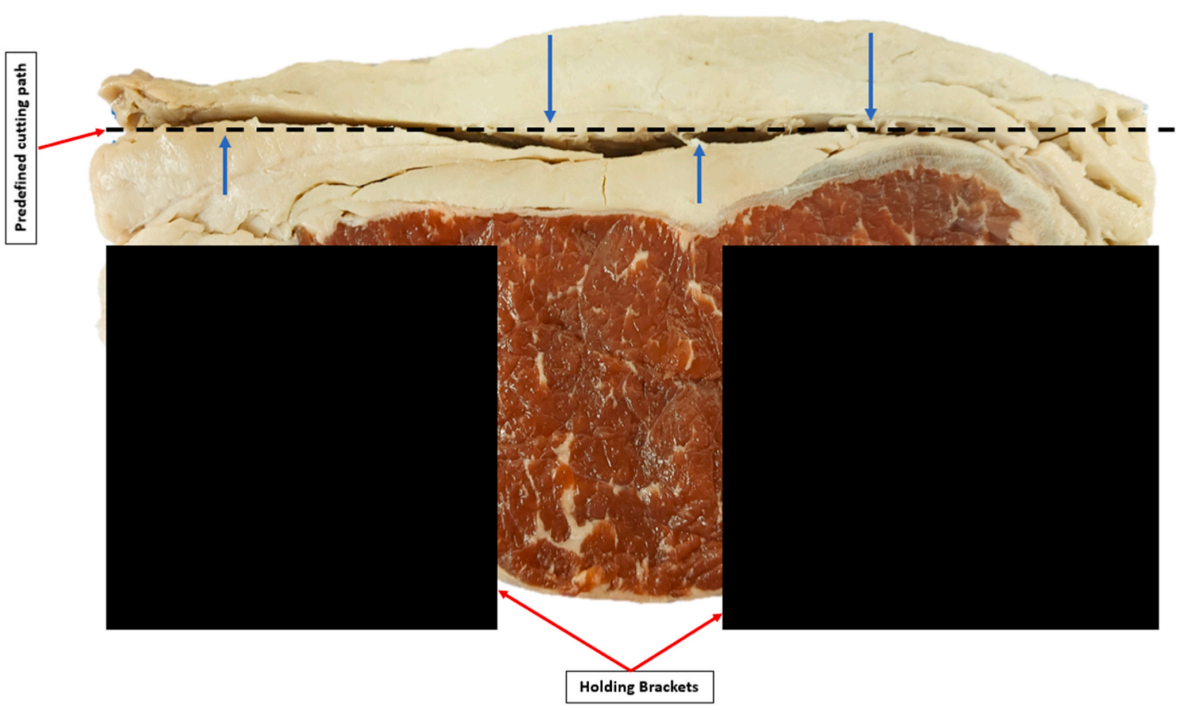


Fig. 11. The fat tissue structure and tissue deformation causing the knife to deviate from the predefined cutting path.

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.

Role of funding source

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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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