Trends in Food Science & Technology 137 (2023) 142–155

Contents lists available at ScienceDirect

Trends in Food Science & Technology

journal homepage: www.elsevier.com/locate/tifs

Robotics and sensing technologies in red meat processing: A review

Basem Adel Aly [a,*], Tobias Low [b], Derek Long [c,a], Craig Baillie [c], Peter Brett [a]

[a] Center for Agricultural Engineering, University of Southern Queensland, Australia
[b] School of Engineering, University of Southern Queensland, Australia
[c] School of Agriculture and Environment Science, University of Southern Queensland, Australia

A R T I C L E I N F O

Keywords:
Robotics
Sensing technologies
Red meat processing
Automation
Cutting tasks
Adaptive control

A B S T R A C T

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 & Grimbsy 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.

* Corresponding author. University of Southern Queensland, Australia.
E-mail address: Basem.Aly@usq.edu.au (B.A. Aly).

[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.

https://doi.org/10.1016/j.tifs.2023.05.015
Received 27 October 2022; Received in revised form 9 May 2023; Accepted 24 May 2023
Available online 25 May 2023

- 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):

- o Intramuscular fat is located within the meat muscle.
- o Intermuscular fat is located between muscles.
- o 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).
- o 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):

- o The connective tissue that covers each muscle is called Endomysiuma and is made of collagen.
- o 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.
- o 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.
- o A percentage of intramuscular fat exists between the muscle bundles (marbling).

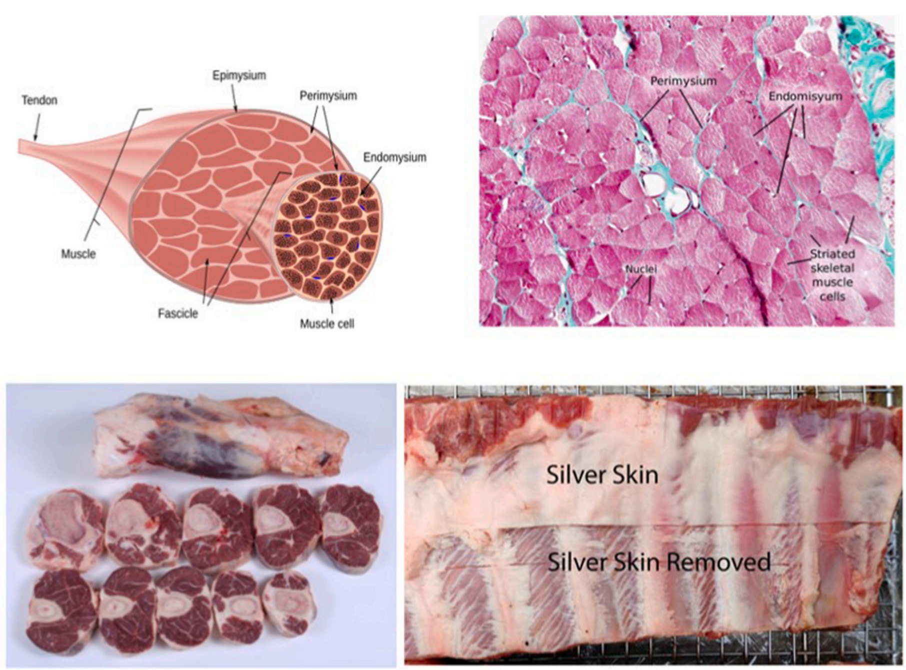

Fig. 1. Muscles' internal structure (Megías et al., 2023).

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 (Megías 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

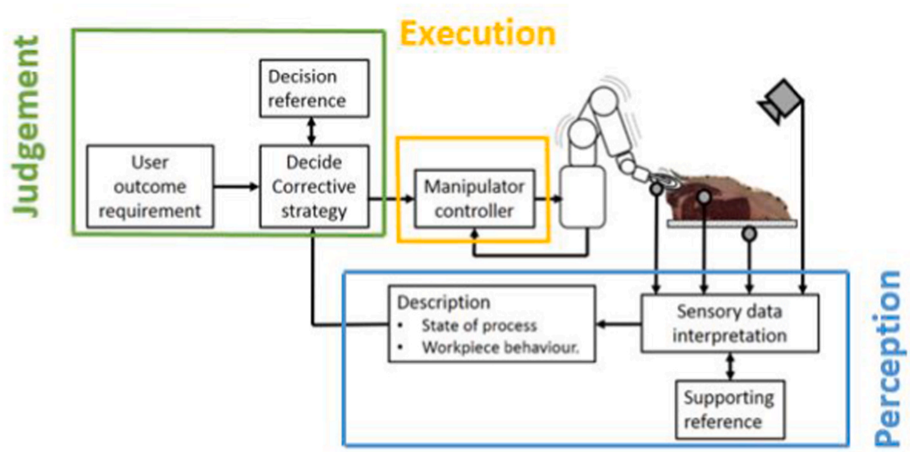

Fig. 2. Control system for automated meat processing (Border, Brett, & Baillie, 2019).

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.)

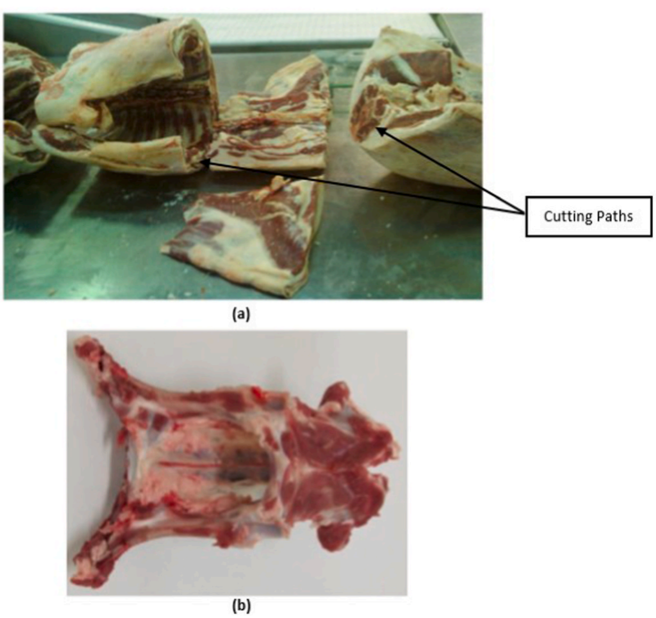

Fig. 4. a) Lamb primal cuts are produced by performing straight cuts (Green et al., 2014), b) The ununiform bone profile for the hindquarter is the cutting path (Maunsell & Scott Technology Ltd, 2018). (For interpretation of the references to colour in this figure legend, the reader is referred to the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

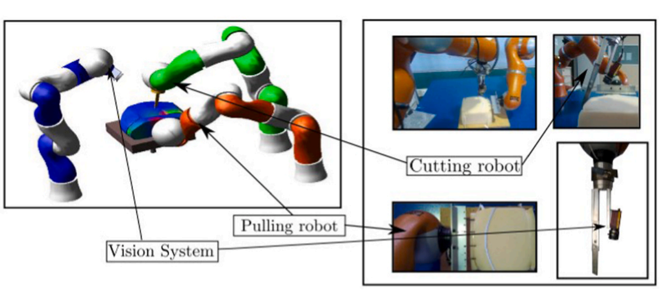

Fig. 5. Experimental rig for beef round muscles separation (Long et al., 2014b).

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

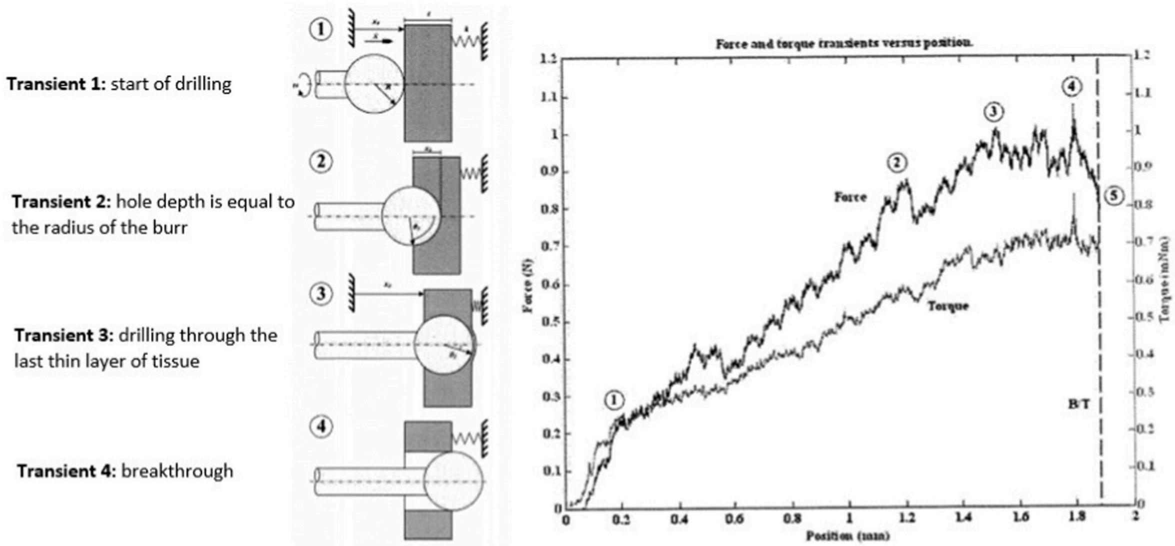

Fig. 6. Force transients during the drilling process (Taylor, 2008).

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 Bailie: Writing-review & editing.

Role of funding source

The research is funded by the University of Southern Queensland international stipend research scholarship and the University of Southern Queensland international fees research scholarship. There is no involvement of any external sponsorship.

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.

Acknowledgment

The authors would like to acknowledge and express appreciation to professor Peter Brett for igniting the idea behind this project and providing inspiration from his vast experience in medical robotics and the Center for Agricultural Engineering (CAE) for providing all the necessary resources for the author to perform the research on the highest level possible.

References

Australian Government Department of Agriculture. (2019). AUS-MEAT capability assessment review. https://www.agriculture.gov.au/sites/default/files/documents/aus-meat-capability-assessment.pdf.

Bader, F., & Rahimifard, S. (2020). A methodology for the selection of industrial robots in food handling. *Innovative Food Science & Emerging Technologies, 64*(102379). https://www.sciencedirect.com/science/article/pii/S1466856420303258.

Border, F., Brett, P., & Baillie, C. (2019). *Automation of uniform fat trimming for the subcutaneous fat profile of beef striploin (Unpublished work)*. University of Southern Queensland.

Border, F., Koodabandehloo, K., & Brett, P. (2019). Robots for complex cutting operations in beef processing. In *Proceedings of the 2019 international conference on machine vision and industrial production (M2VIP)*. Toowoomba, QLD, Australia http://www.m2vip.com/Proceedings/081_beef_cutting.pdf.

Choi, S., Zhang, G., Fuhlbrigge, T., Watson, T., & Tallian, R. (2013). Applications and requirements of industrial robots in meat processing. In *2013 IEEE international conference on automation science and engineering (CASE)*.

Christensen, L. B., & Engell-Nørregård, M. P. (2016). Augmented reality in the slaughterhouse-a future operation facility? *Cogent Food & Agriculture, 2*(1), Article 1188678. https://www.tandfonline.com/doi/full/10.1080/23311932.2016.1188678.

Christensen, H. I., & Ucsd. (2023). Mid-cycle update to the US national robotics roadmap. In *Computing Community Consortium*. https://cra.org/ccc/wp-content/uploads/sites/2/2023/04/Robotics-Mid-Cycle-White-Paper.pdf.

Cook, J., Martchenko, V., Hughes, A., Shirazi, M., Starling, S., & SCOTT Automation and Robotics. (2017). Objective primal measurement (OPM) – pack-off primal pick and pack: Fundamental vision and sensing evaluation. https://www.mla.com.au/contentassets/070b4a8a94aa4e53a972eb7a5390daff/p.psh.0739_final_report_.pdf.

Cotin, S., Delingette, H., & Ayache, N. (2000). A hybrid elastic model allowing real-time cutting, deformations and force-feedback for surgery training and simulation. *The Visual Computer, 16*(8), 437–452. https://inria.hal.science/inria-00615105/.

Delgado-Pando, G., Allen, P., Troy, D. J., & McDonnell, C. K. (2021). Objective carcass measurement technologies: Latest developments and future trends. *Trends in Food Science & Technology, 111*, 771–782. https://www.sciencedirect.com/science/article/pii/S0924224420307287.

Duchemin, G., Dombre, E., Pierrot, F., & Poignet, P. (2003). Robotized skin harvesting. *Experimental Robotics VIII*, 404–413 (Springer).

Foster, A., & Machinery Automation & Robotics Pty Ltd. (2011). Alternative cutting techniques for the meat industry. Meat & Livestock Australia. https://www.mla.com.au/contentassets/11ac8050177e45778e0045d7162ba14c/a.tec.0045_final_report.pdf.

n.d Frontmatec. Automatic rib puller https://www.frontmatec.com/en/pork-solutions/deboning-trimming/automatic-deboning-trimming/automatic-rib-puller.

n.d. Frontmatec. Automatic primal cutting line AGOL-800/1100 https://www.frontmatec.com/en/pork-solutions/primal-cutting/automatic-primal-cutting/automatic-primal-cutting-line-eu

Frontmatec. (2019). Automatic rib puller ARP15. https://www.frontmatec.com/media/3232/frontmatec-automatic-rib-puller-arp15_en.pdf.

Frontmatec. (2020). Robotic belly trimmer with value grading technology. https://www.frontmatec.com/media/6001/frontmatec-robotic-belly-trimmer-rbt-_a4.pdf.

Frontmatec. (2021a). 3D loin trimmer type ALTD-450. https://www.frontmatec.com/media/6499/altd-450-frontmatec-3d-loin-trimmer-gb-v2-2_spread.pdf.

Frontmatec. (2021b). Automatic loin trimmer type ALTL-1100. https://www.frontmatec.com/media/6493/altl-1100-automatic-loin-trimmer-v3-3-gb_spread.pdf.

Frontmatec. (2021c). Fully automatic cutting line Type AGOL-800. https://www.frontmatec.com/media/6498/agol-800-frontmatec-fully-automatic-cutting-line-for-pork-gb-v2-1_print.pdf.
Frontmatec. (2022). Automatic chine bone saw type CBCL-100. https://www.frontmatec.com/media/7090/cbcl-100-automatic-chine-bone-saw-v1-1-gb_spread.pdf.
Green, P., Bryan, K., & Greenleaf Enterprise. (2014). Ex-ante scoping options for LEAP V automated ovine shoulder breakup. Meat & Livestock Australia. https://www.mla.com.au/contentassets/0241f4b18cf24aab96c690ef9d9cfeef/a.cis.0034_final_report.pdf.
Green, P., Bryan, K., Fischer, S., & Greenleaf Enterprises. (2014). LEAP III ovine X ray primal cutting system, Ex post review. Meat & Livestock Australia https://www.mla.com.au/contentassets/170c1cdc955b4f4a96202569a4ae9fff/p.pip.0327_general_leap_iii_ex_post_cba_report.pdf.
Guire, G., Sabourin, L., Gogu, G., & Lemoine, E. (2010). Robotic cell for beef carcass primal cutting and pork ham boning in meat industry. *Industrial Robot, 37*(6), 532–541. https://doi.org/10.1108/01439911011081687
Haidegger, T. (2020). Taxonomy and standards in robotics. In M. H. Ang, O. Khatib, & B. Siciliano (Eds.), *Encyclopedia of robotics* (pp. 1–10). https://doi.org/10.1007/978-3-642-41610-1_190-1. Springer Berlin Heidelberg.
Han, L., Wang, H., Liu, Z., Chen, W., & Zhang, X. (2020). Vision-based cutting control of deformable objects with surface tracking. *IEEE, 26*(4), 2016–2026. https://doi.org/10.1109/TMECH.2020.3029114
IFR International Federation of Robotics. (2021). Executive summary world robotics 2021 industrial robots. https://ifr.org/img/worldrobotics/Executive_Summary_WR_Industrial_Robots_2021.pdf.
International Organization for Standardization. (2002). ISO 14159:2002 Safety of machinery — hygiene requirements for the design of machinery. https://www.iso.org/standard/23748.html.
International Organization for Standardization. (2018). ISO 22000:2018 Food safety management systems — requirements for any organization in the food chain. https://www.iso.org/standard/65464.html.
Jacob, R., & Calnan, H. (2018). Improving lamb lean meat yield: A tehnical guide forthe Australian lamb and sheep meat industry. https://www.mla.com.au/globalassets/mla-corporate/marketing-beef-and-lamb/documents/meat-standards-australia/improving-lamb-lean-meat-yield-interactive-july-2019.pdf.
Kauffman, R. G. (2001). Meat composition. In Y. H. Hui, W. K. Nip, R. W. Rogers, & O. A. Young (Eds.), *Meat science and applications* (pp. 41–60). CRC Press.
Khodabandehloo, K. (2018). Technology evaluation for fat removal for beef striploins leaving a uniform thickness behind. AMPC. https://www.ampc.com.au/getmedia/1785d85f-7abb-4c07-a73b-72f02eb1b161/AMPC_technologyEvaluationForFatRemoval_FinalReport.pdf?ext=.pdf.
Khodabandehloo, K. (2022). Achieving robotic meat cutting. *Animal Frontiers, 12*(2), 7–17. https://doi.org/10.1093/af/vfac012
Kim, J., Kwon, Y.-K., Kim, H.-W., Seol, K.-H., & Cho, B.-K. (2023). Robot technology for pork and beef meat slaughtering process: A review. *Animals, 13*(4), 651. https://doi.org/10.3390/ani13040651
Lonergan, M., Topel, G., & Marple, N. (2019). *Fat and fat cells in domestic animals* (2 ed.). Academic Press. https://doi.org/10.1016/B978-0-12-815277-5.00005-6
Long, P., Khalil, W., & Martinet, P. (2014a). Force/vision control for robotic cutting of soft materials. In *2014 IEEE/RSJ international conference on intelligent robots and systems* (Chicago, IL, USA).
Long, P., Khalil, W., & Martinet, P. (2014b). Robotic deformable object cutting: From simulation to experimental validation. In *European Workshop on Deformable Object Manipulation*.
Luo, S., Bimbo, J., Dahiya, R., & Liu, H. (2017). Robotic tactile perception of object properties: A review. *Mechatronics, 48*, 54–67. https://doi.org/10.1016/j.mechatronics.2017.11.002
Maithani, H., Ramon, C., J, A., Lequievre, L., Mezouar, Y., & Alric, M. (2021). Exoscarne: Assistive strategies for an industrial meat cutting system based on physical human-robot interaction. *Applied Sciences, 11*(9), 3907. https://doi.org/10.3390/app11093907
n.d. Marel. Townsend pork butt trimmer https://marel.com/media/mj0egsol/at-21-620-leaflet.pdf
Marel. (2023a). Primal cutter. https://marel.com/en/products/primal-cutter.
Marel. (2023b). Townsend at 21-620 autotrimmer. https://marel.com/en/products/townsend-at-21-620-autotrimmer.
Mason, A., Korostynska, O., Cordova-Lopez, L., Esper, I., Romanov, D., Ross, S., et al. (2021). Meat Factory Cell: Assisting meat processors address sustainability in meat production. In *2021 IEEE 21st international symposium on computational intelligence and informatics (CINTI)*.
Mason, A., Romanov, D., Cordova-Lopez, L., & Korostynska, O. (2022a). Smart knife: Integrated intelligence for robotic meat cutting. *IEEE Sensors Journal, 22*(21), 20475–20483. https://doi.org/10.1109/JSEN.2022.3208667
Mason, A., Romanov, D., Cordova-Lopez, L. E., Ross, S., & Korostynska, O. (2022b). Smart knife: Technological advances towards smart cutting tools in meat industry automation. *Sensor Review, 42*(1), 1–12. https://doi.org/10.1108/SR-09-2021-0315
Maunsell, S., & Scott Technology Ltd. (2018). Lamb boning leap 2 (hindquarter) Australian site ready prototype. Meat & Livestock Australia. https://www.mla.com.au/contentassets/34bcfaa31799496da6f24c264c3b4c34/p.psh.0736_final_report.pdf.
Mayekawa Mfg. (2016). Mayekawa/wandas-rx. https://www.youtube.com/watch?v=LxgPpF3VAWI&ab_channel=MAYEKAWAMFG.
Meat & Livestock Australia. (2020). State of the industry report 2020. https://www.mla.com.au/globalassets/mla-corporate/prices–markets/documents/trends–analysis/soti-report/mla-state-of-industry-report-2020.pdf.
de Medeiros Esper, I., Cordova-Lopez, L. E., Romanov, D., Alvseike, O., From, P. J., & Mason, A. (2022). Pigs: A stepwise RGB-D novel pig carcass cutting dataset. *Data in Brief, 41*(107945). https://www.sciencedirect.com/science/article/pii/S2352340922001561.
de Medeiros Esper, I., From, P. J., & Mason, A. (2021). Robotisation and intelligent systems in abattoirs. *Trends in Food Science & Technology, 108*, 214–222. https://www.sciencedirect.com/science/article/pii/S0924224420306798.
Megías, M., Molist, P., & Pombal, M. (2023). *Atlas of plant and animal histology*. University of Vigo. https://mmegias.webs.uvigo.es/02-english/index.html.
Merenkova, S., Zinina, O., Khayrullin, M., Bychkova, T., & Moskvina, L. (2020). Study of the rheological properties of meat-vegetable minces. IOP conference series: Earth and environmental science, MLA, & AMPC. (2008). Fat composition of beef & sheepmeat: Opportunities for manipulation. In *Meatupdate. csiro. au.* https://meatupdate.csiro.au/data/MEAT_TECHNOLOGY_UPDATE_08-2.pdf.
Mosnier, J., Berry, F., & Ait-Aider, O. (2009). A new method for projector calibration based on visual servoing. MYCOM Global. (2020). *Deboning machines*. In *MVA 2009 IAPR international workshop on machine vision applications* https://www.mayekawa.com/products/deboning_machines/.
Nabil, E., Belhassen-Chedli, B., & Grigore, G. (2015). Soft material modeling for robotic task formulation and control in the muscle separation process. *Robotics and Computer-Integrated Manufacturing, 32*, 37–53. https://doi.org/10.1016/j.rcim.2014.09.003
Pathak, V., Singh, V., & Sanjay, Y. (2011). Ultrasound as a modern tool for carcass evaluation and meat processing: A review. *International Journal of Meat Science, 1*(1), 83–92. https://doi.org/10.3923/ijmeat.2011.83.92
Paxman, J. L., D, Wu, P., & Dissanayake, G. (2006). Cobotics for meat processing. Meat & Livestock Australia. https://www.mla.com.au/research-and-development/reports/2006/cobotics-for-meat-processing/.
Prieto, N., Pawluczyk, O., Dugan, M. E. R., & Aalhus, J. L. (2017). A review of the principles and applications of near-infrared spectroscopy to characterize meat, fat, and meat products. *Applied Spectroscopy, 71*(7), 1403–1426. https://doi.org/10.1177/0003702817709299
Purnell, G., & Grimbsy Institute of Further & Higher Education. (2013). Robotics and automation in meat processing. Elsevier *Robotics and Automation in the Food Industry*, 304–328. https://doi.org/10.1533/9780857095763.2.304.
Purnell, G., & Brown, T. (2004). Equipment for controlled fat trimming of lamb chops. *Computers and Electronics in Agriculture, 45*(1–3), 109–124. https://doi.org/10.1016/j.compag.2004.06.004
Romanov, D., Korostynska, O., Lekang, O. I., & Mason, A. (2022). Towards human-robot collaboration in meat processing: Challenges and possibilities. *Journal of Food Engineering.* , Article 111117. https://doi.org/10.1016/j.jfoodeng.2022.111117
Ross, S., Korostynska, O., Cordova-Lopez, L., & Mason, A. (2022). A review of unilateral grippers for meat industry automation. *Trends in Food Science & Technology, 119*, 309–319. https://doi.org/10.1016/j.tifs.2021.12.017
Ruberg, C. (2021). Pursuit of the world's best steak-advanced robotics and X-ray technology to transform an industry. *The Journal of Applied Business and Economics, 23*(4), 257–270. http://www.na-businesspress.com/JABE/JABE23-4/20_RubergFinal.pdf.
Schumacher, M., DelCurto-Wyffels, H., Thomson, J., & Boles, J. (2022). Fat deposition and fat effects on meat quality—a review. *Animals, 12*(12), 1550. https://doi.org/10.3390/ani12121550
Scott Technology Limited. (2013). Scott - automated lamb boning system 2013. https://www.youtube.com/watch?v=za2dsB0qrMg&ab_channel=ScottTechnologyLimited.
Scott Technology Limited. (2022). Robotic beef rib cutting. https://scottautomation.com/assets/Sectors/Meat-processing/Resources/Beef-Processing/Beef-Rib-Cutting-Scribing-Brochure-EN.pdf.
Sg Heilbron Economic & Policy Consulting. (2018). Analysis of regulatory and related costs in red meat processing. In *Australian Meat Processing Corporation*. https://australianabattoirs.com/wp-content/uploads/2019/03/FINAL_Cost_to_Operate_Report_Oct_2018.pdf.
Sheridan, J., Allen, P., Ziegler, J., Marinkov, M., Suvakov, M., & Heinz, G. (1994). *Guidelines for slaughtering, meat cutting and further processing*. FAO. http://www.fao.org/3/T0279E/T0279E00.htm.
Sødring, M., Thauland Håseth, T., Rasten Brunsdon, E., Bjørnstad, P., Sandnes, R., Røtterud, O., et al. (2022). Effects of meat factory cell on pork qualities, sensory characteristics and carcass hygiene: An exploratory study. *Acta Agriculturae Scandinavica, Section A—Animal Science*, 1–16. https://doi.org/10.1080/09064702.2022.2113120
Starling, S., & Robotic Technologies Limited. (2011). Automated lamb bone-in forequarter processing system – stage 1. https://www.mla.com.au/contentassets/a28fcb137e724d11a5552f8741ec5f93/p.psh.0520_final_report.pdf.
Subrin, K., Alric, M., Sabourin, L., & Gogu, G. (2011). A robotic cell for pork legs deboning. https://digicomst.ie/wp-content/uploads/2020/05/2011_13_05.pdf.
Takács, K., Mason, A., Christensen, L. B., & Haidegger, T. (2020). Robotic grippers for large and soft object manipulation. In *2020 IEEE 20th international Symposium on computational Intelligence and informatics (CINTI)*.
Takács, K., Mason, A., Cordova-Lopez, L. E., Alexy, M., Galambos, P., & Haidegger, T. (2023). Current safety legislation of food processing smart robot systems the red meat sector. In *arXiv preprint arXiv:2304.14014*. https://doi.org/10.48550/arXiv.2304.14014
Taylor, R. P. (2008). Development and deployment of an autonomous micro-drilling system for cochleostomy Aston University]. https://ethos.bl.uk/OrderDetails.do?uin=uk.bl.ethos.497362.
Toldrá, F. N., & Leo, M. L. (2006). *Advanced technologies for meat processing* (1 ed.). CRC Press. https://doi.org/10.1201/9781420017311

Toyoshima, K., Umino, T., Matsumoto, K., Goto, O., & Kimura, K. (2016). Development of automatic deboning robot for pork thigh. *The Japan Society of Mechanical Engineers*. https://www.jsme.or.jp/jsme/uploads/2016/11/awardn13-2.pdf.

UNECE. (2004). Bovine meat carcases and cuts. https://unece.org/DAM/trade/agr/standard/meat/e/Bovine_2004_e_Publication.pdf.

Valsta, L., Tapanainen, H., & Männistö, S. (2005). Meat fats in nutrition. *Meat Science, 70*(3), 525–530. https://doi.org/10.1016/j.meatsci.2004.12.016

Wood, J., Enser, M., Fisher, A., Nute, G., Sheard, P., Richardson, R., et al. (2008). Fat deposition, fatty acid composition and meat quality: A review. *Meat Science, 78*(4), 343–358. https://doi.org/10.1016/j.meatsci.2007.07.019