Final Report

AI Beef Cutting

Artificial Intelligence - Non-X-ray Beef Cutting - Stage 2 (Intelligent Robotics)

Public Report

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1.0 Executive Summary

The first iteration of beef scribing at NCMC (**Semi-Automated Scribing development**) initially targeted fully automatic placement of cut lines using pattern matching with colour images. This approach was ultimately unsuccessful in terms of reaching an acceptable level of accuracy and a semi-automatic approach was adopted. Machinery Automation and Robotics (MAR) then worked with **JBS** (funded by MAR, JBS, AMPC, MLA & the Australian Federal Government) to evolve this concept into an automated solution using x-ray imaging. The solution details can be located at this link - **Automated Scribing development** and is still in operation at JBS today.

While the non-x-ray system at NCMC wasn't able to reach full automatic operation using just colour imaging, the advancement of artificial intelligence and machine learning technology in the past ten years presents a significant opportunity to enable a solution which doesn't require x-ray technology.

With this in mind, AMPC sought input from solution providers around an innovation theme exploring alternative sensing approaches for beef scribing. The primary goal for this innovation theme is a successful development(s) to enable automation of beef cutting activities without having to rely on x-ray imaging. This would enable a lower cost and potentially smaller footprint solution that one requiring x-ray imaging. It is expected that there will be some sacrifice in accuracy, but the magnitude of this is not yet understood.

As a result, the objective of this project is to evaluate possible designs for non-x-ray Automated Beef cutting systems (in terms of sensing design, neural network and algorithm design) and to report on the potential accuracy and reliability of such as system, to determine feasibility of the design.

Intelligent Robotics approached the project by first developing a preliminary sensing concept design for a 'non-x-ray beef scribing system'. From this design, site trials were performed to acquire sensing data. This was done over two trials spread across two plants, with two different sensing setups. The first trials focused on identifying the spine cuts only, while the second trials focused on identifying the rib scribing cuts while building upon the results from the first trials to further examine spine cut positioning. Once the data were acquired a number of neural networks were then trialled to find the optimal setup for accurately predicting these features.

The results obtained suggest that neural networks offer a feasible sensing alternative for beef scribing to x-ray sensing. With respect to the spine cuts, the ability to accurately identify the required features using the neural networks as a first pass for the vision analysis is feasible and will increase in performance with greater training. Regarding the vertical rib cuts, the neural network already operates at a level similar to a highly trained operator in identifying the key features. The networks also operate very successfully at correctly identifying features which have been historically challenging to identify reliably in previous attempts at vision-based scribing.

This project has therefore shown it is possible to identify the key features required to characterise the beef scribing cuts without using x-ray sensing. The next phase of development in both instances would be to now develop the further post-processing vision algorithms to transform these features into actual cut paths, as well as adding further refinement and error checking tools to ensure robust performance.

While there is still a significant amount of vision code to be developed to produce robust, production-quality software, the key risks for AI-based scribing have been examined within this project and the optimal methodology identified to achieve the desired results. It is therefore envisioned that this work would continue under a project for a commercial AI-driven beef scribing system with an Australian beef processing facility. Intelligent Robotics and AMPC are currently working with Australian beef processors to further develop the technology in production beef scribing systems.

2.0 Introduction

The first iteration of beef scribing at NCMC (**Semi-Automated Scribing development**) initially targeted fully automatic placement of cut lines using pattern matching with colour images. This approach was ultimately unsuccessful in terms of reaching an acceptable level of accuracy and a semi-automatic approach was adopted.

Machinery Automation and Robotics (MAR) then worked with **JBS** (funded by MAR, JBS, AMPC, MLA & the Australian Federal Government) to evolve this concept into an automated solution using x-ray imaging. The solution details can be located at this link - **Automated Scribing development** and is still in operation at JBS today.

While the non-x-ray system at NCMC wasn't able to reach full automatic operation using just colour imaging, the advancement of artificial intelligence and machine learning technology in the past ten years presents a significant opportunity to enable a solution which doesn't require x-ray technology.

AMPC's 2020-2025 Strategic Plan identifies both within the Advance Manufacturing (pages 5 & 6) and People and Culture (pages 10 & 11) programs that:

1. Removing staff from dangerous operations, via Hands-Off processing (Adv. Mft.),
2. Carcase Primal Profitability Optimisation, via accurate processing (Adv. Mft.)
3. Digitisation, via acquiring product information and leveraging data insights (Adv. Mft.),
4. Attraction, via demonstration and developing a wide range of operations (People & Culture),
5. Retention, via improving working conditions and making tasks exciting (People & Culture),
6. Development, via developing tasks that require higher skills and intellect – operational & technical (People & Culture),
7. Safety and Wellbeing, via reducing the high-risk nature of processing operations (People & Culture),

are all foci of AMPC, and that this one innovation theme will aim to make a significant impact upon all seven.

As such the primary goal for this innovation theme is a successful development(s) to enable automation of beef cutting activities without having to rely on x-ray imaging. This would enable a lower cost and potentially smaller footprint solution that one requiring x-ray imaging. It is expected that there will be some sacrifice in accuracy, but the magnitude of this is not yet understood.

This project involved understanding what a "non-x-ray automated cutting system" may look like, particularly in terms of sensing technologies and geometry. Once this was understood, the required sensing equipment was procured and setup at a processor site for a large number of carcase images to be acquired. These images were analysed with a number of neural network algorithms. The accuracy able to be achieved was reported, as well as next steps for the development.

3.0 Project Objectives

This project involved understanding what an AI enabled “non-x-ray automated cutting system” may look like, with particular emphasis on the sensing technology. X-ray has been used in a large range of meat cutting projects in the past, and it is a proven technology for the automation of meat cutting systems to a reasonable degree of accuracy. Unfortunately, there are drawbacks to the use of X-ray for this purpose, that include:

1) Required size
    a. The required size of an automation cell to build a labyrinth of x-ray shielding is too much for many sites
2) Cost
    a. Addition of X-ray introduces a large number of costs
3) Complexity
    a. Component complexity increases when having to use high voltage components
4) Risk
    a. There is an increased risk due to radiation exposure

Due to the reasons above, there are numerous of benefits to the development of an AI powered automated cutting system. This project has also been identified to be in line with AMPC’s 2020-2025 strategic plan, with benefits including:

1) Removing staff from dangerous operations, via hands-off processing.
2) Increasing safety and wellbeing, by reducing the high-risk nature or certain processing operations.
3) Attraction of people to the industry via demonstrating a wide range of technological operations.
4) Retention of people within the industry by improving working conditions.
5) Development, via developing tasks that require higher skills and intellect.
6) Increasing carcase primal profitability through optimisation
7) Enabler for acquiring product and processing formation in order to leverage data insights.

As a result, the objective of this project is to evaluate possible designs for non-x-ray Automated Beef cutting systems (in terms of sensing design, neural network and algorithm design) and to report on the potential accuracy and reliability of such as system, to determine feasibility of the design.

4.0 Methodology

The methodology for conducting the project was as follows:

1. Preliminary sensing concept design for a ‘non-x-ray cutting’ system
2. Perform on-site trials to acquire a large amount of carcase images, emulating the sensing setup of the concept as closely as possible
3. Use the data to teach and verify a number of artificial intelligence models to determine the most promising
4. Assess the accuracy that is achievable using this method
5. Report on next steps in the development pathway

5.0 Project Outcomes

During the course of the project, a sensing concept was developed for an AI-based beef scribing system. This sensing design was then used to design a trial rig to allow sensing data to be captured on-site in the same relative geometry.

The first concept consisted of the camera in a certain position relative to the other hardware in an envisioned scribing system. The data taken from this geometry were analysed and run through a number of neural networks. It was found that this geometry was satisfactory for identification of the spine cuts. Consistent identification of rib cuts however was challenging.

A second data capture trial was performed at a second meat processing facility with the camera in a different geometry. Neural network algorithms were developed to identify the key features for characterising the rib scribing cuts. The results from the first round of data acquisition trials were also build upon to examine characterisation of the spine cuts. The spine feature detection accuracy on the second dataset was comparable to that of the first dataset. However it was much more robust in dealing with obstructions due to redundancy which was built into the algorithms, resulting in a more robust system.

In order to train the neural networks to identify the rib scribing features of interest, an experienced operator was used to label these points on the images acquired. The consistency of the operator was also assessed by randomly repeating 50 images within the whole dataset 3 times at random intervals throughout the 3-day labelling exercise. The repeatability of the operator was then compared with the accuracy of the results from the neural network for the prediction of these points.

The results obtained suggests that neural networks offer a feasible sensing alternative for beef scribing to x-ray sensing.

6.0 Discussion

6.1 Preliminary Design of Non-X-ray Scribing Sensing Solution

The design of the sensing solution is intended to emulate the sensing environment of a concept non-X-Ray Scribing System. The purpose of the preliminary sensing design is to prepare for data collection trials performed within the project. This data will enable us to begin the development of the image processing algorithms necessary for AI feature detection required for non-x-ray scribing.

Two cameras were to be setup to allow for two images of the same carcase to be taken. The carcases will be free-hanging and travelling along an overhead chain. This will enable capturing the data with slight movement occurring between the two images, to allow for a greater dataset as well as potential verification activities exploring slight differences in carcase presentation.

To facilitate image capture at the two imaging stations, two portable image acquisition rigs were designed to capture colour images of beef carcases as they move along the overhead conveyor. The rigs were designed to replicate the position of the camera relative to the beef carcases as would be expected in a production scribing system, as well as the high intensity and diffuse lighting conditions which exist in meat processing plants. The cameras were triggered by laser distance sensors, to facilitate efficient data collection from a moving overhead conveyor in a production environment.

The rigs were positioned approximately 2 meters apart.

Laser Distance Sensors

The laser distance sensors are used to trigger the cameras to acquire an image as a carcase enters the field of view. The sensors have been set up to trigger send a trigger when the carcase passes completely passes the laser beam. This is done to ensure that the red laser is not visible by the camera during acquisition.

Figure 1- Laser distance sensors.

Camera

The camera needed to meet the following requirements:

1) Colour – To make it easier on the operators to label the carcases.
2) High resolution – to ensure that sufficient accuracy is achievable in the labelling and cutting process.
3) High signal to noise ratio – to reduce noise level.
4) High dynamic range – to provide larger range of pixel intensity values for more accurate image analysis.

5) Gigabit ethernet – a reliable camera interface.
6) External trigger – to allow for external sensor to trigger the camera.

To meet these requirements two industrial colour cameras were selected for image acquisition.

Figure 2- 5MP colour camera.

Lens

The camera lenses were chosen to suit the imaging sensor size and resolution, and to provide the field of view required at the desired focal distance. The aperture size was calculated and adjusted to be large as possible to increase the amount of light that can reach the sensor while maintaining the target depth of field to ensure that all the carcase is in focus.

Lighting

Lights were selected for the following requirements:

1) High intensity – to reduce exposure time and thus reduce motion blur.
2) Uniform – to ensure that whole carcase is evenly illuminated.
3) Diffuse – to reduce hot spots due to point sources of light.

To meet these requirements, high-intensity lights were chosen as the light source. Each camera rig is fitted with two lights which produce the required light intensity at the target carcase distance.

Junction Box

A junction box was built to house a 24V power supply to power the cameras and laser distance sensors. The junction box also contains the electrical wiring for the laser distance sensors to trigger the cameras.

Figure 3- Junction box and connected devices.

Rig Design

Each rig consisted of an aluminium extrusion frame to support two high intensity lights, a Colour camera and a laser distance sensor. The LED battens and camera are attached to the vertical section, while the laser distance sensor is attached to the horizontal arm.

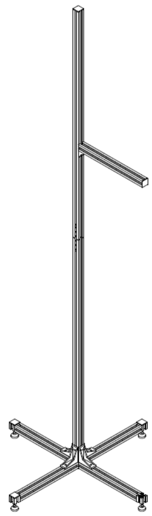

Figure 4- Aluminium extrusion camera, sensor and light rig.

Adjustable aluminium brackets were designed to mount the camera and laser distance sensor to the aluminium extrusion frame and to allow for easy adjustment of their position. The camera brackets can be adjusted vertically along the length of extrusion and it also supports a 1/4” ball-head camera mount so that the roll, pitch and yaw of the camera can be easily adjusted.

The laser distance sensor is mounted on the horizontal arm and allows for horizontal and yaw adjustment.

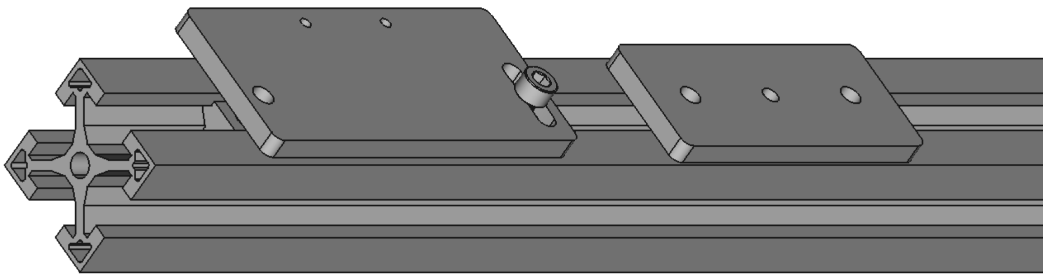

Figure 5- Laser sensor (left) and camera (right) brackets.

Programming

Computer code was written to asynchronously capture and save images from both cameras whenever a hardware trigger is received. Images are saved at full resolution. The images are saved into a folder along with a timestamp and camera ID so that images of the same carcase can identified easily from both cameras for future analysis.

6.2 On-site Trials

The trialling rig was installed at a beef processing facility.

Laser Configuration

The laser distance sensor was used to trigger the camera to capture as a carcase enters the field of view. The sensor was configured to send a trigger when the carcase completely passes the laser beam. This is done to ensure that the red laser is not visible by the camera during acquisition. The sensor was configured to ignore any beam obstructions that occur out of the range of the carcase so that operators working in that area would not trigger the camera unnecessarily. Due to the regular stopping of the overhead conveyer and the resulting swinging of the carcases, a timeout delay was added to the sensor to ignore multiple triggers occurring in a short period of time and unnecessarily capturing multiple images.

Camera Configuration

The focal distance, aperture size and exposure time are key parameters that directly affect the image quality. First, the aperture and focal distance were adjusted.

Once all the camera parameters were configured, the aperture and focal distance were locked in place with grub screw on the lens and the taped up to prevent them from becoming loose during the trial.

Camera Calibration

To make it as easy as possible for the neural network to learn from our images, it is important to remove/minimise any unnecessary distortions/diversity. During this trial we have gone to great lengths to reduce all forms of unnecessary distortion including:

1) Using laser distance sensor to capture an image of the carcase as the same location.
2) Reducing motion blur by stabilising the carcase as it move past the camera
3) Using intense and uniform lights to ensure that carcases are always well lit and that the images are not affected by external lighting.

Another form of distortion that needs to be addressed is due to lens distortion. The camera lens produces a form of distortion that warps the image near the edges, making straight lines appear curved. This type of distortion causes features to distort differently depending on their vertical or horizontal position in the image.

A camera calibration was performed to remove common forms of lens distortion from the image. The calibration process involves taking hundreds of images of a calibration board at many different positions. A calibration algorithm detects the markers on the calibration board and uses their location along with the geometry of the calibration board to calculate all the camera parameters. These camera parameters can later be used to remove the lens distortion from the images taken on-site.

Image Acquisition

Over the period of four days on site a total of 1919 images were captured for training the AI model. Approximately 14% of the images were unusable for the following reasons:

1. False triggering caused by operator,
2. Duplicate images due to prolonged conveyor stoppages,
3. Operator in the images still working on carcase,

4. Rotated carcase, obscuring areas of interest,
5. Significant motion blur.

6.3 Initial Data Analysis and Further Data Collection

The data collection process outlined previously was used to collect data at one Australian red meat processor. In this data collection trial, the cameras were located in a position based on the first concept design. However, early in the data analysis, we recognised that the camera placement is not ideal for the identification of some features necessary to place some of the scribing cuts – specifically, the rib scribes.

To address this issue, the concept was redesigned and a second data collection trial was conducted at a second Australian red meat processor. A total of 3492 images were collected.

The data from both image collection trials were processed within the project.

6.4 Further Data Analysis

AI Output requirements

The purpose of the AI system is to identify a set of key features that will later be used by the vision processing software in a post-processing stage to accurately define spine and rib scribes according to a given specification.

Spine Scribes

To define accurate spine cut paths for the robot, the required features were identified.

To identify these features, neural network models were developed to output results which accurately and consistently characterised these features for post-processing vision tools to then be used to calculate cut paths in 3D space.

Rib Scribes

Since the rib scribe specification varies across sites, for this project rib scribing networks have been tailored specifically for the cut specification of the second meat processing site. However, the output of the neural networks was designed to be general enough that it can be easily used for a broad range of cut specifications across the Australian red meat industry.

To meet the target cut specification, a number of different types of neural networks were developed.

By combining the output of the rib and spine scribing networks, all the information necessary is available to calculate all the cut paths by simply processing the image masks with traditional machine vision tools.

Data Analyses

Data from both sites was partitioned into training, validation, and test sets. The training sets consist of approximately 300 images all collected on a single day and are used to directly train the neural networks. The validation sets (consisting of approximately 60 images), are used to evaluate the performance of the networks during the training process. Finally, the test sets consist of all remaining images (1000+). The test images are not involved in the training process in any way and are used as an unbiased evaluation of the network performance once the training is complete. Furthermore, using a large test set allows for the system to be tested on a broad range of images, across multiple days of data collection with varying camera positions, lighting and triggering sensor positions.

Once the data were partitioned, they were labelled by manually indicating on the images the features which were to be identified by the neural network. These features would then allow a cutting system to identify and generate the cut profiles required for a robot to perform the required cuts.

Training

To prepare the labelled data for training, the data was split into two groups – a training set (80%) and a validation set (20%). A range of neural network models were developed to predict the position of the labelled features from the colour image data. Each network was trained on the training set and the results validated on the validation set. Each network was trained until there was no noticeable improvement in the validation results. This process was repeated for each network until the best network topology and the best set of parameters were converged upon.

The neural network contains millions of parameters whose values can be learnt during the training process. However, there are other hyper parameters that cannot be learnt during the training process. These hyper parameters include things like the topology of the network, neuron activation functions, batch size, and many other aspects.

Cross validation was used to identify a set of “ideal” hyper parameters. This process involves training the neural networks many times with different hyper parameter sets, and then selecting and tuning those that improve prediction accuracy and learning rate.

Spine Cut Identification Network

The data from the first data acquisition trial were used for assessing the identification of spine cuts. A single neural network was developed to predict the features of interest. All further image processing can then be focused on analysing the image masks as they capture enough information identify the cutting paths.

To address the common forms of failure from the spine cut identification results, it was decided to modify the neural network to detect additional features. The rationale for this decision was to add a level of redundancy to the predictions of the neural network.

Rib Cut Identification Network

The data from the second data acquisition trial were used for assessing the identification of rib cuts. In this instance, multiple neural networks were developed.

The assistance was sought from a skilled operator to label the required features for characterising the rib scribing cuts on approximately 1200 images. This data was then randomly split into a training and validation set and the remaining data was used as a test set.

As mentioned earlier, it was established that the camera position used in the first data collection trial was unsuitable for accurately detecting the rib features for predicting the position of the rib scribes. To address this issue, in the second data acquisition trial the camera placed in a different geometry.

6.5 Neural Network Testing

Spine Cut Assessment – First Data Acquisition Trial

The data used for testing was collected on a separate day from the training and validation data and consisted of 877 images. The result produced by the neural network is processed to generate an image overlay to illustrate all detected features.

The results were compiled by manually inspecting all the image results produced by the neural network.

There are number of factors that affect the accuracy of our model. Such factors include:

1. Number of training samples. The more training data we have the more accurately the model can learn.
2. Labelling accuracy. The model can only learn from the training data. So, if there are inaccuracies in the labelled training data, then the model may not converge correctly.
3. Image quality. Ideally the carcass would be stationary or moving in a more controlled manner as the images are captured. This would have resulted in sharper images enabling us to see features in greater detail.
4. Lighting. A more intense light source would have allowed us to reduce the exposure on the camera to remove motion blur, and it would also allow us to close the aperture further to improve the sharpness at a larger depth of field.
5. Product presentation. In many cases, there was fat and blood covering the areas of interest, making it impossible to directly detect key features. Approximately 10% of the carcasses have broken back, with beaks occurring between vertebrae 11-18. In all cases, soft sides did not affect the placement of the scribing marks.

All these factors would be addressed in a production system to maximise the accuracy of our model, particularly the product presentation considerations which can be addressed with the appropriate error checking functionality and employing contingency vision processing in the event an error or inconsistency is detected. One mechanism for this was trialled in the second data acquisition trial.

Considering only the unobstructed images, there were a small number of incorrect predictions. In all cases however, the detection was able to be detected with basic error detection code. We are confident that the detection accuracy of the features can be improved by addressing some of the factors listed above.

Spine and Rib Cut Assessment – Second Data Acquisition Trial

The spine feature detection accuracy on the second dataset was comparable to that of the first dataset. However, in the rare event where a feature was missed due to an obstruction, redundant information was present, so predicting both these features will result in a more robust system.

The first 12 ribs were detected in every image. In 100% of images the first rib was found correctly. The rib accuracy was as good, and if not better, than the accuracy of the labelled data which was placed by an experienced operator. In a few cases where there was a large discrepancy between the labelled and predicted results a closer inspection revealed that the data was incorrectly labelled. This demonstrates that the network was able to generalise well and learn the general concept of a rib despite some incorrectly labelled training/validation data.

Rib Cut Feature Prediction

To evaluate the prediction accuracy of the neural network, we compare the network prediction with the target labels placed by an experienced operator. To perform this comparison, 50 images were repeated 3 times at random intervals through the 3-day labelling exercise. Data from these 50 repeated images allows us to estimate the repeatability of the operator.

The operator repeatability vs neural network accuracy for the x and y position of the features were statistically analysed. The results showed that the neural network produced a comparable error margin compared to the operator repeatability. It should be noted that the target label being used to evaluate the accuracy of the neural network would also have an error margin similar to that of the operator repeatability. Therefore, the error distribution of the neural network should be thought of as an upper bound over the true prediction error distribution.

6.6 Development Pathway

The results obtained suggest that neural networks offer a feasible sensing alternative for beef scribing to x-ray sensing. With respect to the spine cuts, the ability to accurately identify the desired features using the neural networks as a first pass for the vision analysis is feasible and will increase in performance with greater training. Additional post-processing of the neural network result would also be coded to ensure correction of any missed feature results (something already handled well with the redundancy of the two separate networks looking for different features independently but can be further bolstered by standard vision processing tools such as bounds checking) and defects such as broken backs. The next steps for development would further include developing the computer vision algorithms which isolate the features of interest more accurately at a pixel level to be able to then place the scribing cut line as required by the specification. This can be achieved with standard vision processing once the correct features have been isolated by the neural networks. It is anticipated that the average accuracy of this operation can be achieved well within the required target – the key risk to the accuracy of the placement of this cut is miscounting of certain features, which the neural networks already appear to cope with quite robustly.

Regarding the vertical rib cuts, the neural network already operates at a level similar to a highly trained operator in identifying the key points. The networks also operate very successfully at correctly identifying rib 1 and counting the first 12 ribs – another key limitation from previous attempts at vision-based scribing. This ensures that the correct ribs will be cut which was identified as a key risk if x-ray imaging is not utilised. Further vision processing algorithms will then be developed to offset the brisket cutting line to place the dorsal cutting line, and defining the start and end points of these cuts. It is known from previous work that this can be done quite simply and accurately with the vision processing algorithms, ensuring the two ribs cuts are parallel and to the correct width – the key value drivers for performing these cuts.

The key risks for AI-based scribing have been examined within this project and the optimal methodology identified to achieve the desired results.

7.0 Conclusions / Recommendations

This project sought to evaluate the feasibility of using AI to identify key features for the purposes of characterising beef scribing cuts without the use of x-ray sensing. A preliminary sensing concept design was developed for a 'non-x-ray cutting system' and this design was used to design site trials to acquire sensing data. This was performed in two stages. The first stage involved acquiring data from one Australian red meat processor with the camera in a certain position based on an initial concept design for the purpose of identifying the spine scribe cuts. The second stage involved acquiring data from a second Australian red meat processor with the camera placed in second geometry based on another concept design in order to identify the rib scribes as well as the spine scribe features of interest. After performing these trials, the data from both trials were segmented, labelled and analysed. A number of neural network algorithms were trialled before settling upon those which yielded the most promising results. The accuracy achieved from these analyses were reported upon within the project.

The results obtained suggest that neural networks offer a feasible sensing alternative for beef scribing to x-ray sensing. With respect to the spine cuts, the ability to accurately identify the features of interest using the neural networks as a first pass for the vision analysis is feasible and will increase in performance with greater training. Regarding the vertical rib cuts, the neural network already operates at a level similar to a highly trained operator in identifying the key points characterising the rib scribes. The networks also operate very successfully at correctly identifying rib 1 and counting the first 12 ribs – another key limitation from previous attempts at vision-based scribing.

This project has therefore shown it is possible to identify the key features required to characterise the beef scribing cuts without using x-ray sensing. The next phase of development in both instances would be to now develop the further post-processing vision algorithms to transform these features into actual cut paths, as well as adding further refinement and error checking tools to ensure robust performance.

The key risks for AI-based scribing have been examined within this project and the optimal methodology identified to achieve the desired results. It is therefore envisioned that this work would continue under a project for a commercial AI-driven beef scribing system with an Australian beef processing facility. Intelligent Robotics and AMPC are currently working with Australian beef processors to further develop the technology in production beef scribing systems.