Final report

Final Report for Artificial Intelligence (AI) Cattle Recognition Pilot. (P.PSH.1263)

Project code: P.PSH.1263 Artificial Intelligence (AI) Cattle Recognition Pilot

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Abstract

This project was undertaken to find an improved solution for the registration and identification of cattle in Australia using computer video-based technologies: in short, a more economical and reliable solution as a potential replacement for NLIS tags.

Video data is being collected (now almost a year) from the water troughs in a feedlot. These videos have been annotated and processed using tracking and facial recognition algorithms with the support of a research team at Australian National University (ANU). The pilot has demonstrated that video-based registration and recognition is accurate if sufficient frontal face images can be obtained. Other recently published research by University of New England (UNE) has reached similar conclusions (https://www.mdpi.com/2073-4395/11/11/2365). The challenge of capturing sufficient front facing images in a timely manner without constraining the cattle has proven difficult. Current collection techniques result in only a small proportion of the images being useful to train the computer models (~3%). A method is needed to reliably capture front facing images of cattle in the field for this to be a practical solution.

The results in this study suggest there is a potential for a low-cost replacement for NLIS tags however this was not realised in this project.

Based on the number of unexpected challenges and lessons learnt around the facial recognition working in a commercial setting, it was agreed by the project team that an alternative project be scoped with additional partners involved. This new project will focus on the additional research to achieve a method to ensure that cattle face a camera when required for video registration and recognition. This will require specialists in animal behaviour as well as the existing team of computer vision experts.

Executive summary

Background

The Australian red meat industry has a global reputation as a supplier of clean, safe and natural product, underpinned by its disease-free status and advanced food safety and integrity systems. To maintain competitive advantage, the red meat industry must pursue and invest in new technologies and approaches to integrity that address current and future customer requirements, maximise value and improve uptake across the industry. Integrity Systems Company (a subsidiary of MLA) (ISC) has a vision of a fully automated supply chain, and this project aligns with its strategic target of real-time traceability.

Lumachain already has traceability systems in operation from animal arrival at abattoir to end customer in several markets: e.g., a bag or box of meat can be scanned in real time and the complete journey and history of that meat is revealed on a web-browser or mobile application. Identifying and tracking animals on the farm during their life and up until their arrival at the abattoir is an extension of this traceability further back in the supply chain. The Lumachain roadmap plans to provide full traceability of an animal from 'paddock to plate'. Major progress has been made in primary processing (abattoir) part of the supply chain with traceability and production enhancement solutions in implementation for major producers both in Australia and globally – full traceability is from reception of the animal to secondary processor including the delivery journey. Projects are also in progress for the subsequent parts of the supply chain - first implementations in secondary processing and retail traceability.

The aim of the project was to conduct a proof-of-concept pilot using Artificial Intelligence (AI), and video images and advanced computer software algorithms to enable cattle recognition and automatically trace individual animals without the need for National Livestock Identification Scheme (NLIS) tags. This project is the first part of providing a complete solution that provides animal life traceability up to entry to primary processor, thus completing the supply chain 'paddock to plate' traceability.

Project Objectives

The original project objectives were:

1. A database of at least 50 individual cattle on three selected properties (identified in collaboration with ISC and Food Agility CRC) will be established such that the AI system can recognise each animal and link it to its on-farm grower information records. Cattle on-farm movements will be used to track animals to test and demonstrate the system accuracy. Suitable cameras will be installed on the farm to track and identify animals.
2. Cameras will be installed at the sale yard (access facilitated in collaboration with ISC and Food Agility CRC) used by these properties, and the system will identify the cattle individually as each enters the sale yard and display the growth/ provenance information from the property records entered.
3. A presentation and video demonstration covering the on farm and sale yard trials will be developed.
4. The project will consider the scalability of the technology across a full commercial cattle supply chain in Australia (birth to processing of cattle).
5. The project will produce a preliminary commercial viability statement for users of the system (producers, sale yards, processors).
6. The project will produce a preliminary statement on any changes to work methods and the practicality of the system for users (producers, sale yards, processors), e.g. the time it takes to scan and register cattle, time taken to read and identify cattle at unload points, particularly whether unreasonable delays will be experienced.

7. The results of the pilot will be written up in a final report, including a summary report to share with industry and a full confidential report for ISC.

Methodology and Outcomes

This project commenced in September 2020 – the detailed objectives, timelines and methodology have varied considerably due to Covid constraints and learnings as the work progressed. See Section 2 of the detailed report.

The overall objective did not alter and is still the same – that of cattle recognition using video-based technologies as a replacement for NLIS tags.

Video of cattle was collected in a feedlot over several months with the camera positioned over the water trough. Lumachain have learnt from this pilot, video-based cattle identification requires a significant number of frontal face images for registration and recognition. The collection method provided less than ~3% of useful frames. While high accuracy can be achieved with sufficient frontal images, the true challenge is to have cattle face a camera to collect sufficient images for registration or identification in a reasonable timeframe. While this can be done by restraining cattle in a crush this is not a practical replacement for NLIS tags. To be successful a method must be found to obtain frontal face images of cattle reliably in a feedlot, at saleyards, on arrival at abattoirs and eventually in the field.

This project has achieved confidence that cattle recognition is possible with sufficient front-face images. The practical problem to be solved to be an NLIS replacement is how to achieve cattle frontal facial images reliably without intervention (e.g., crush).

Recommendations

This pilot has given confidence that accurate recognition is possible with sufficient facial images. Other work at UNE also has demonstrated this (https://www.mdpi.com/2073-4395/11/11/2365).

The true research problem to make video recognition a practical solution is:

Development of a method to achieve that cattle face a camera when required for registration and identification for application in animal traceability.

This research is outside the scope and capabilities of this project team hence this project is being terminated. It is proposed to apply for funding for a new project specifically to research an alternate method to achieve this outcome with the assistance of specialists in animal behaviour and computer vision specialists used on this project.

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1. Background

The Australian red meat industry has a global reputation as a supplier of clean, safe and natural product, underpinned by its disease-free status and advanced food safety and integrity systems. To maintain this competitive advantage, the red meat industry must pursue and invest in new technologies and approaches to integrity that address current and future customer requirements, maximise value and improve uptake across the industry. Integrity Systems Company (an MLA subsidiary) (ISC) has a vision of a fully automated supply chain, and this project aligns with it's strategic target of real-time traceability.

The aim of the project was to conduct a proof-of-concept pilot using Artificial Intelligence (AI) to enable cattle recognition using video images and advanced computer software algorithms to automatically trace individual animals without the need for NLIS tags.

AI is a computer-based technology/software that interprets patterns and behaviour into data and insights. Combined with machine learning, you can teach the program what to look for, thereby providing a specific functionality, such as traceability. Using computers to monitor and record animal movements could greatly reduce human labour and costs associated with NLIS compliance.

This project funded a proof-of-concept using Lumachain's technology for cattle traceability. Several benefits were to be investigated:

- Proof of concept cattle identification using Artificial Intelligence (AI) facial/ body recognition in a commercial environment, and
- Automation of integrity data capture for individual cattle transfer through the value chain to reduce the risk of human error, speed up communication and improve auditing processes.

If the proof-of-concept was successful, there was to be a producer demonstration at MLA's AGM in November 2020 to seek feedback and then a larger program of work was expected to be scoped for funding.

2. Objectives

The table below outlines the original project objectives and whether these were successful or not achieved prior to termination of this project.

Original Objective	Achievement Commentary
1. A database of at least 50 individual cattle on three selected properties (identified in collaboration with ISC and Food Agility CRC) will be established such that the AI system can recognise each animal and link it to its on-farm grower information records. Cattle on-farm movements will be used to track animals to test and demonstrate the system accuracy. Suitable cameras will be installed on the farm to track and identify animals.	A database of over 200 cattle in one feedlot has been achieved. Only one feedlot was used due to (1) a costly specialist solar powered video station was required; and (2) lack of properties to participate.
2. Cameras will be installed at the sale yard (access facilitated in collaboration with ISC and Food Agility CRC) used by these properties, and the system will identify the cattle individually as each enters the sale yard and display the growth/ provenance information from the property records entered.	Not achieved. This was part of Milestone 3 and the project was terminated beforehand.
3. A presentation and video demonstration covering the on farm and sale yard trials will be developed for Red Meat 2020 (MLA AGM) (17-19 Nov 2020 in Toowoomba). Discussions will be held with attendees to seek endorsement for the direction and progress to date.	Not achieved. In person conference did not proceed due to COVID.
4. The project will consider the scalability of the technology across a full commercial cattle supply chain in Australia (birth to processing of cattle).	This is the objective still – hence the termination of this project and a new project proposal to find a practical registration solution to the cattle image capture challenge.
5. The project will produce a preliminary commercial viability statement for users of the system (producers, sale yards, processors).	Not completed as the solution is still in development. This will be done through a subsequent project.
6. The project will produce a preliminary statement on any changes to work methods and the practicality of the system for users (producers, sale yards, processors), e.g., the time it takes to scan and register cattle, time taken to read and identify cattle at unload points, particularly whether unreasonable delays will be experienced.	Not achieved as the solution is still in development. However, the new proposed project will develop cattle behaviour-based methods to achieve reliable front facing images. If Lumachain can solve this there will be a practical solution possible. This will include changes to work methods, yet to be defined.
7. The results of the pilot will be written up in a final report, including a summary report to share with industry and a full confidential report for ISC.	This final deliverable report will cover the pilot results completed to date and will be used as summary report to share with industry.

3. Methodology

Original Approach: The proposed approach for this milestone was to collect video footage and photos of 50+ cattle at each of 3 properties, AI trained, cameras installed and tracking cattle at each property.

Approach Adopted: This changed as Lumachain progressed and learnt more, and was provided in email and video updates on the project.

The actual approach adopted to date has been:

1. collect video footage of a batch (200-240) of black angus cattle in a feedlot pen at Australian Country Choice (ACC) Opal Creek (200-240) and train the AI model, firstly for tracking and secondly for identification; and
2. collect a second database of another batch of black angus cattle at the same feedlot and apply the identification algorithm to measure and demonstrate the accuracy.

The next step in the development would be to test the AI with a further batch of cattle, and then test it in a different environment (e.g. saleyard) and with a different breed of cattle. The mobile solar powered video station can be re-deployed if required for this purpose.

The main drivers for the change in methodology are:

- The method and manner required to effectively capture video footage of cattle:

  Lumachain trialed collecting video footage of cattle going through races for registration which was the original plan. However, from a development perspective this was not suitable as there was too much head movement and the time of transit too rapid (too few frames for initial training of the AI algorithm). To capture suitable video, while not disturbing the cattle and do this in a remote location, Lumachain had to design and develop a solar powered video station. This took longer than planned due to trialing and testing, and further complicated by Covid restrictions in terms of site access and equipment delivery. It is expected that once the algorithms are refined that they will work on cattle races and in the field, but video captured in this way was not suitable for initial development.

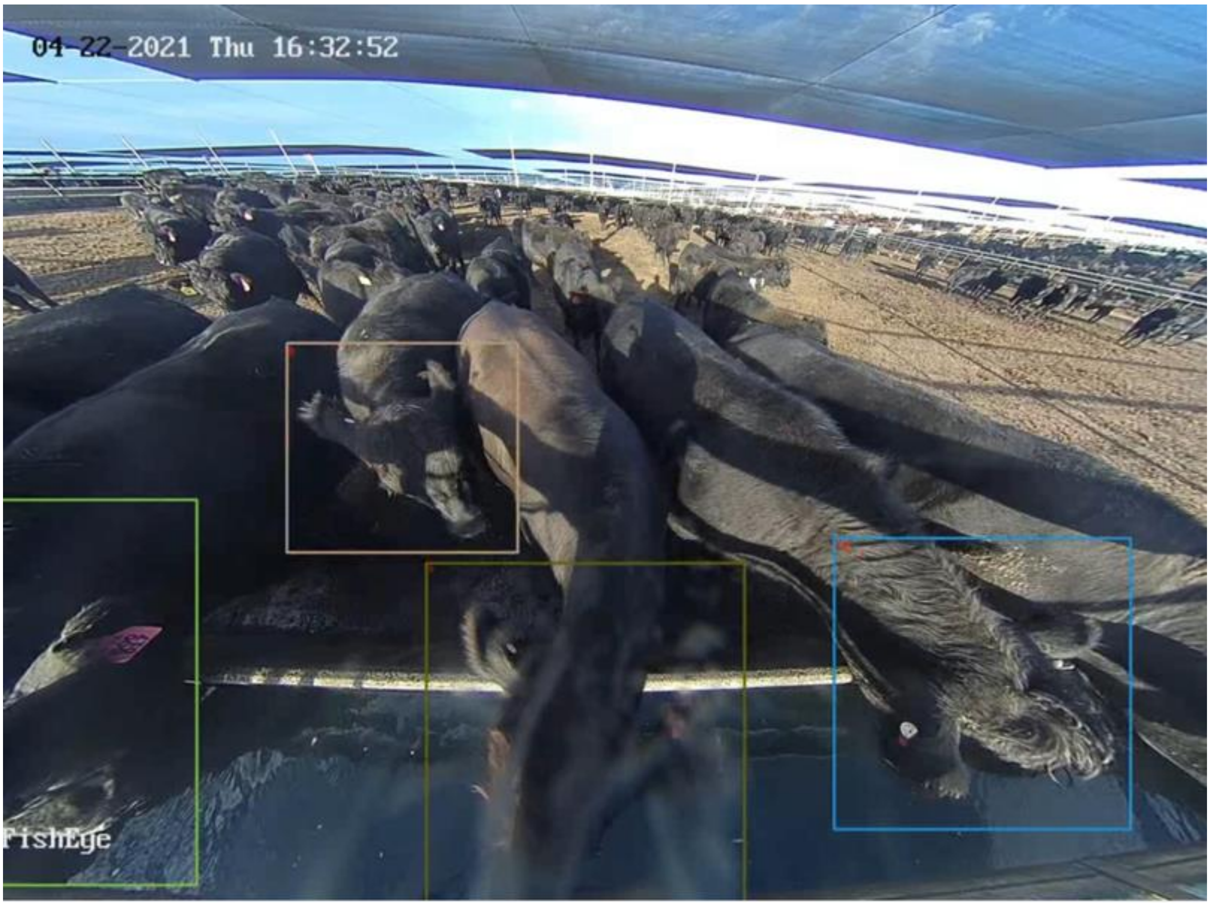
- The number and type of sites for the technology development:

  At the start of the project MLA's assistance to identify properties and a saleyard to participate in the trial was sought and this resulted in only one property for the initial trials in the cattle races. Once it was realised that capturing video in races was not going to work for the development phase, along with the cost of the equipment for each location and the duration of recording required. A decision was made to use multiple batches of cattle at one location to develop and prove the technology.

- Data analysis from videos of tracked animals:

  By first developing temporal tracking technology each animal is not required to be recognised in every video frame. This technology tracks an animal in a video as it moves providing a tracking record of frames for a particular animal. Animals can thus be tracked over time and then the identification algorithm is only applied on video frames where there is a clear view of the animal's face thereby increasing the probability of correct identification. Analysis of the tracking results demonstrated that the view of the animal is suitable for recognition in only a small percentage of frames. This has guided the placement of the video cameras in the feedlot and improved data annotation for training the AI algorithms, currently underway.

The reality and cost of the video collection station meant that resources were only available to collect on one feedlot. This feedlot had primarily angus cattle and given that they were completely black without obvious distinguishing features this was seen as a challenge for the technology. If the algorithms work with black angus, there is high confidence that they will work on other cattle groups that have more facial diversity – see photo below.



- The technical approach that was followed is:

Once the raw videos were collected video annotation proceeded in three stages to provide data with the aim of training an animal identification algorithm.

1. Selected video frames were manually annotated with bounding boxes around each animal's head as shown in the figure above. Once sufficient frames were annotated (over 8,000 in this study spanning 33 different video clips) Lumachain moved onto the second stage of training.
2. In the second stage, an automatic head detection and tracking algorithm was developed. Here a state-of-the-art multiple object tracker (Zhang et al., IJCV 2021) algorithm was used which has been shown effective in pedestrian tracking. In a small number of cases the tracker erroneously merged two different animals into the same tracklet, a problem known in the multi-object tracking community as 'identity-switch'. However, the quality of the tracker output was determined to be good enough to move on to the last annotation stage. This provided a tracklet dataset for multiple animals.
3. In the third stage the automatically detected tracklets were shown to a human annotator to assign unique animal identifiers to each track. Here the annotator would scan through frames included in the track looking for clearly visible ear tags. The number on the ear tag was then assigned to every detected bounding box in the track (whether or not the ear tag was visible in the other bounding boxes or not). This resulted in nearly 2,000 tracklets being manually annotated containing 204 unique animals, an average of 10 tracklets per animal, to create the dataset used for training the animal identification algorithm as described in the following section.

4. Project outcomes

Tracking algorithms for cattle faces have been developed along with algorithms to individually identify cattle. The producer feedlot left ear tag numbers have been used to validate the accuracy of the algorithms.

Achieving acceptable identification accuracy has progressed and identification accuracy of 17% at milestone 2 has been achieved, which is short of the 90% Milestone 2 target with a number of image capture and quality issues frustrating higher accuracy. The annotated tracklet data (as described in the previous section) was split into a training dataset of 1,473 tracklets (82,326 frames) and an evaluation dataset of 439 tracklets (21,141 frames). The training dataset is used to train the model and once trained this model is tested on the evaluation dataset. A state-of-the-art model for person re-identification (Mang et al., TPAMI 2021) was adopted as the architecture for animal identification and trained on the training dataset by taking every 20^{th} frame to avoid near duplicates in neighbouring video frames. Initial results show a tracklet-wise recognition accuracy of 17.3% and this is well above 0.49% which would be random guessing.[1] Whilst this is well below the 97.5% target for replacing NLIS tags, it is well above random and with refinement in the proposed future project, higher accuracy will be achieved.

Analysis indicates that the primary sources of error that need to be addressed to improve the identification accuracy are:

- poor quality frames (e.g., motion blur and dirt on the camera lens);
- poor alignment of bounding boxes around the animal's head for classification, and
- animal not looking directly towards the camera. For example, in many cases the bounding boxes are around the animal's neck rather than face. Further work is needed to develop automatic methods for discounting these frames during training and tracklet identification.

5. Conclusion

5.1 Benefits to industry

Discussion with MLA and some parts of the industry has resulted in awareness of the project amongst MLA staff and producers. The feedback has been overwhelmingly positive albeit with some skepticism – support is strong for a practical lower maintenance alternative option using images instead of the NLIS tags. However, this will require high level of accuracy.

In the discussions with producers there is even more enthusiasm for the potential extension of this technology into animal performance monitoring, which would be a future project and extension to this work.

Once the animal identification is working with reasonable accuracy, Lumachain believe that a major value will be continuing the research into animal growth rates and health monitoring using computer vision AI. This data will be of great value to identify any sick animals early and any signs of animals with low growth rates. It will also enable selection for market as early as possible and be able to draft aside out of spec cattle rather than them arriving at the abattoir and being discounted. This data will also be able to be linked to breeding and feeding histories for further industry improvement.

[1] As a point of reference random guessing would achieve an accuracy of 0.49% (i.e., 1 in 204).

5.2 Future research and recommendations

Video has been collected in feedlots of cattle at the drinking trough over several months. Lumachain have learnt during this pilot video-based cattle identification requires a significant number of frontal face images for registration and recognition. The collection method provided less than 5% of useful frames. While high accuracy can be achieved with sufficient frontal images, the true challenge is to have cattle face a camera to collect sufficient images for registration (50-100) or identification (<5). While this can be done by restraining cattle in a crush this is not a practical replacement for NLIS tags and for animal performance monitoring and tracking. To be successful a method must be found to obtain frontal face images of cattle reliably in a feedlot, at saleyards, on arrival at abattoirs and eventually in the field.

Termination Reason

This pilot has given confidence that accurate recognition is possible with sufficient facial images. Other work at UNE also has demonstrated the potential (https://www.mdpi.com/2073-4395/11/11/2365).

The research problem that needs to be solved to make video recognition a practical solution is:

Development of a method to achieve that cattle face a camera when required for registration and identification.

This research was outside the scope and capabilities of the current project team hence this project is being terminated. It is proposed to apply for funding for a new project specifically to research a method to achieve this outcome with the assistance of specialists in animal behaviour and computer vision specialists.