Automated Visual Inspection and Preparation of Live Animals for Meat Processing

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1.0 EXECUTIVE SUMMARY

This project was intended to investigate and develop advanced technologies for automated pre-slaughter inspection and preparation of live animals. In the first year of the project, RMIT University was engaged by the Australian Meat Processor Corporation (AMPC) to undertake an extensive literature review on existing computer vision-based technologies for automated visual inspection of livestock. Target technologies were related to assessing appearance characteristics of livestock, and categorised into monitoring of locomotion, size, weight and behaviour of livestock. The technology assessment was based on evaluating the effectiveness in terms of various factors such as accuracy, correct classification rate, level of automation, and applicability for a specific livestock or circumstance. Each technology was compared with other relevant technologies within its own group. The technology comparison also included a technical review of hardware and software requirements. For software requirements, a range of techniques, algorithms and methodologies for image processing tasks of the monitoring technology were reviewed. For hardware, the review was more focused on various types of general-purpose imaging devices (active/passive, measurement principles, vision sensor technologies, etc.) that were used, or have the potential to be used, for visual inspection of livestock. In addition, various vision-based livestock monitoring technologies involving different positions of the imaging input device in the overall monitoring system and different critical specifications (resolution and frame rate) of the imaging device, were compared.

The results of our literature review show that automated visual cleanliness inspection of livestock (except for cow teats) has not received much attention in literature. To address AMPC concerns regarding the freedom to operate (FTO) in this area, we conducted an extensive patent search on the prior art that described livestock washing and cleaning systems, and investigated if computer vision technology was used in those inventions, for determining the cleanliness of livestock. Patents that identified dirt on different surfaces were also identified and analysed. Our patent review showed that the existing livestock washing/cleaning systems appear to have not incorporated the computer vision technology for the purpose of inspecting the external appearance of livestock for cleanliness prior to slaughtering. In addition, the patents for technologies that detect dirt on surfaces disclosed methods that appear to have different scope compared to the scope of this project (live animal inspection for cleanliness). Also, the scope of existing computer-vision based livestock monitoring systems does not appear to include automatic inspection of livestock for cleanliness (except for cow teats) and those are largely limited to the measurement of animals' physical attributes.

To identify the best possible combination of technologies for efficient and automated cleanliness inspection of livestock (our next milestone), we first visited five major meat processing plants in different Australian states. Our visits to those slaughterhouses confirmed that the pre-slaughter processing of lambs does not include washing the animal. As such, our reports were focused on the visual cleanliness inspection of cattle only. Different cleanliness scoring systems were investigated, analysed and compared with Australian meat processing practices in different states. The industry priorities in terms of cleanliness scoring at the time of slaughter were verified with QA experts in our visits, which include minimisation of animal stress as well as potable water consumption during the inspection and cleaning tasks. Improvements in communication and record keeping practices also appear to be highly valued by the industry practitioners. Platforms suitable for delivering visual livestock inspection and/or performing the cleaning action in one location were researched and a suitable combination of technologies to target the industry priorities was proposed.

We extended our investigations on the variations in cleaning processes nationally by visiting seven other major meat processing plants in three different states (Victoria, Queensland and South Australia). Our visits aimed to identify the existing cattle inspection practices as well as collections of sample images of dirty and clean cattle, which were essential for evaluation of the proposed image classification method. Our discussions with QA managers during meat processing plant visits confirmed that the current cleanliness inspection at the pre-slaughter stage is a classification problem in which the visually inspected animal should be categorised into different classes of cleanliness. As such, we devised an image classification methodology that enables classification of different sections of animal hide into one of the following cleanliness categories: clean, dirty, and dagged.

In the next milestone, different designs for implementation of the visual inspection and cleaning actions in one location were investigated, and two different designs were considered for prototype testing; a design that involved a rack of nozzles that is actuated parallel to the side of the cattle and a design that consists of a fixed matrix of nozzles that cleans the same area. We concluded that the nozzle matrix design would realise non-invasive cleanliness inspection, pose minimal stress to cattle, and reduce potable water consumption and wash time. It is also estimated to be cheaper compared to the other considered design.

Moving on to our next milestone, we developed, manufactured, and successfully tested an automated cattle inspection/cleaning system (based on the nozzle matrix design) that utilises optical cameras to detect possible contamination on livestock hides, and applies water to clean visually contaminated sections on the animal before being slaughtered. To automate the cleanliness inspection process, we devised an image classification framework that enables classification of different sections of animal hide into clean, dirty and dagged categories. Each section is analysed by an image classification algorithm to determine its cleanliness status (clean or dirty) from the texture information of the animal skin. Once a section is identified as dirty by the image classification software, targeted washing of the associated area on the animal hide would commence. The automated washing system sprays potable water via specific nozzles that are associated with dirty sections.

We tested the performance of the targeted washing system on live cattle, in a dairy farm located in Albury-Wodonga, Victoria. To this end, an animal ethics application was first submitted to, and approved by RMIT University's Animal Ethics Committee (AEC) to ensure that animal welfare requirements were met. The results of the field experiments verified the system performance, and showed that the system is capable of significantly reducing the visible dirt on the animal skin.

To investigate the feasibility of the integration of additional measurements to the developed inspection/cleaning station prototype, we integrated multi-dimensional data from advanced sensors such as Kinect into the system overall software design and implementation. Measurable characteristics of cattle as well as the specification of hardware and implementation details of software that have been used to realise those measurements in existing cattle monitoring systems were investigated by undertaking an extensive literature and patent review on methods that have the potential to be implemented on our developed cattle inspection/cleaning station prototype. The integrated system was designed based on the above investigations, and additional software and hardware implementations to integrate the measurements into the system were carried out.

2.0 INTRODUCTION AND BACKGROUND LITERATURE

Cattle entering the knocking box of a slaughterhouse often contain external contamination on their hides. The overarching purpose of this research project was to design and develop an automated cattle inspection and washing station that improves the cleanliness of cattle prior to entering the knocking box. This included the development and testing of an appropriate image classification methodology to classify animals in terms of cleanliness for slaughter. The methodology was designed to replicate the common industrial inspection practices across different Australian slaughterhouses. The objective also included the development and evaluation of possible designs that implement the required washing action as well as performing additional measurements related to cattle in tandem with the automated cattle washing prototype that we developed for the preparation of the animals for slaughter.

Studies have shown that various bacteria and contamination carried on the dirty hide of cattle entering the abattoir can be transferred to the carcass of the animal, particularly along the cutting lines of the hide as shown in Figure 1. One such study (Byrne et al., 2000) examined the importance of washing cattle before slaughter. The study consisted of smearing the rump area of 30 heifers with fresh faeces containing an antibiotic resistant strain of Escherichia coli (E. coli) 24 hours before a controlled slaughtering. The 30 heifers were split into three groups. In the first group ten of these cattle entered the normal slaughtering process without any washing or attempts to remove the infected faeces. The second group consisted of ten of the remaining cattle that were washed for one minute with a power hose at 15L of water/minute prior to slaughtering. The remaining ten cattle (group 3) were washed in a similar manner to group 2 with the longer duration of three minutes (Byrne et al., 2000).

The washing treatment applied to group 2 produced a visibly clean animal but upon testing, similar levels of E. coli to an unwashed animal from group 1 remained. The longer duration washing administered in group 3 significantly reduced the detectable levels of E. coli on the cattle hides. Testing the butchers' hands and tools provided a similar result. On some tools washing for 1 minute appeared to increase the amount of E. Coli spread. This is consistent with studies suggesting that E. Coli spreads more rapidly in wet environments. However, washing the animals for 3 minutes (group 3) significantly lowered the level of faecal contamination. The results found in this study suggest that washing for certain durations can provide a significant protection against the spread of E. Coli from dirty animals to the produce in the slaughter process (Byrne et al., 2000).

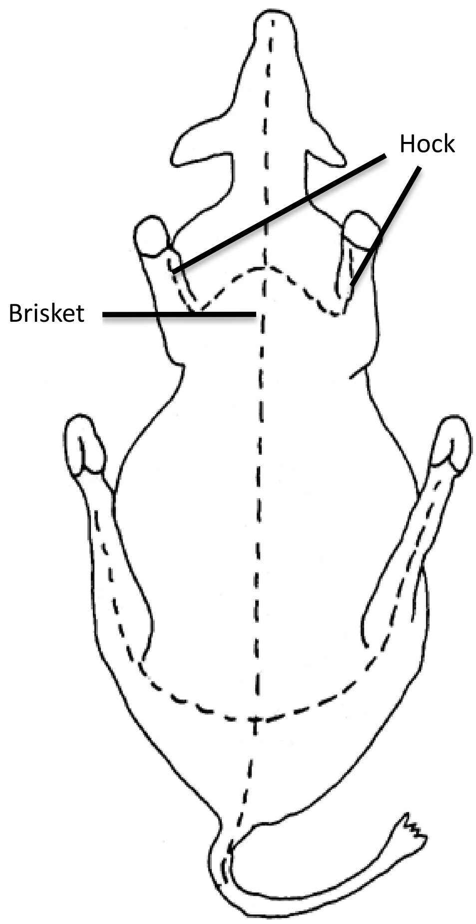


Figure 1. Typical cut paths during slaughtering [http://www.fao.org/docrep/004/t0279e/T0279E32.gif].

Another study examined the correlation between the observed cleanliness of a cattle's hide and the total viable counts (TVCs) measured on the carcass after the hide has been removed (McEvoy et al., 2000). The cattle were visually inspected prior to the slaughtering process and assigned a category ranging from 1 to 5 with 1 being very clean and 5 being very dirty (Table 1). Animals assigned the ratings 2, 3 and 5 were slaughtered and TVCs were taken at five sites on the carcass; the hock, the brisket, the cranial back, the bung and the inside round. The category 4 animals were split into two groups for the second experiment. These animals were slaughtered in separate ways. The first group was slaughtered using the standard slaughtering method while the second group was slaughtered with the butcher's tools being frequently sanitised.

The TVCs taken at the brisket for category 5 and category 3 were significantly higher than category 2 samples. Similarly, the TVCs taken at category 5 on the hock were significantly higher than the category 2 samples. There was no noticeable difference between the recorded TVCs for categories at the cranial back, the bung and the inside round. The second experiment showed that the TVCs at the brisket were significantly lower on the cattle slaughtered using the "clean" tools. However, there was no significant difference in the TVCs taken at the hock between the two groups. The findings from this study do suggest a correlation between the level of cleanliness of the cattle entering the abattoir and the contamination on the resulting carcass (McEvoy et al., 2000). In particular, the differences between the cleaner and dirtier animals at the hock and the brisket indicate that contamination is likely to be spread to the carcass from the hide at the location of the cutting.

Table 1. Cleanliness definitions for the cattle's state of cleanliness (McEvoy et al., 2000).

State of Cleanliness	category
No evidence of adherent faecal matter and limited amounts of loose straw/bedding.	1
A light covering of dried faecal matter and limited amounts of loosely adherent straw/bedding.	2
A significant amount of loose straw/bedding/dirt over a large body area.	3
Heavy amounts of adherent dirt/faeces on fore and hind legs, underside of the abdomen and the lower surface of the ribcage.	4
Very heavy amounts of adherent dirt/faeces. Balling of adherent dirt/faeces may be evident on the underside of the abdomen.	5

Common methods of cleaning cattle involve manual hand washing or open loop systems such as sprinklers in a lairage (WESCOMBE, 1994). At the end of the standard initial washing process, the cattle are visually inspected and manually washed with a hose if any residual contamination is found. An efficient design for livestock washing and cleaning systems should reduce the contamination on livestock bodies and also consider animal welfare issues at the same time. Bulk washing systems such as swim washes have been traditionally used for washing the exterior parts of animals. However, those systems are not efficient in reducing the amount of contamination, mainly because those methods increase the risk of cross contamination and also cause significant stress to the animal (John, 2005) // IPC code: A22B7/00, A22B5/08, A22B5/00 //.

Our review of the relevant literature showed that the cleaning of cattle before slaughter has the potential to reduce the risk of contaminating bacteria and viruses being present in the slaughtering process and transferring to the cattle carcasses. By providing an automated system to provide additional washing with potable water at the final stage, the risk of contamination can be reduced and consistent levels of treatment can be applied to the animals entering an abattoir.

To design an automated cattle inspection and washing station in line with the industry best practices, we investigated the variations in cleaning processes nationally by visiting seven major meat processing plants (see Table 2) in three different states (Victoria, Queensland and South Australia). Those visits confirmed that the industry priorities include the following:

- Inspection and cleaning actions must be carried out in such a way that the animal stress is minimised.
- Animal pre-slaughter washing processes in slaughterhouses commonly include two stages. In the first stage, recycled water is used to perform an initial wash of the animal. In the

second stage, potable water is used to perform the final washing of the animal (this step is also mandatory for export to some jurisdictions including the EU). The use of potable water is a significant expense for the industry. Therefore, they seek to minimise the potable water consumption. Excessive use of potable water would also affect the plants' sustainability. Efficient (controlled) use of potable water in the second (final) stage of washing is a high priority in the meat processing facilities.

// The animal inspection and cleaning is an arduous task and has to be performed outdoors in all weather conditions. Automation of inspection and cleaning processes is viewed favourably by the industry for improving its work practices as well as reducing its manual labour and maximising productivity.

// Record keeping in the harsh outdoor environment of a slaughterhouse is difficult and error-prone. Improvements in communication and record keeping practices appear to be highly valued by the industry, particularly for quality assurance purposes.

As such, we designed and developed an automated cattle inspection and washing station that enabled targeted washing of cattle at the final washing stage. The developed prototype of the station provided a more consistent level of animal treatment. Important considerations in the design and development phase were the animal welfare and the levels of stress that could be generated by the automated targeted washing. Details of the considered designs as well as the final developed prototype that satisfied the above-mentioned requirements and priorities of the Australian meat industry are elaborated on in section 3.0.

Table 2. List of visited meat processing plants.

Plant's Name	State
Teys Australia, Brisbane	QLD
JBS Australia PTY Ltd.	QLD
Kilcoy Pastoral Company	QLD
Radfords Warragul	VIC
Teys Australia, Naracoorte	SA
Thomas Foods	SA

3.0 PROJECT OBJECTIVES

The objectives of this project (according to the research agreement) are outlined as follows:

// Conduct, and submit to AMPC, a comprehensive literature review on existing computer vision techniques for automated inspection. The survey will also include techniques that might have potential to be used for animal inspection but have not yet been exploited for those purposes.

// Conduct, and submit to AMPC, an in-depth patent analysis to ascertain intellectual property developments of computer vision techniques with potential for automated animal inspection.

- Identification of the best possible combination of technologies for delivering the inspection and performing the cleaning action in one location.
- Development of appropriate measures to quantify and classify animals with those measures in terms of readiness for slaughter.
- Verification of the above measures with the industry best practice, ensuring that the proposed measures cover the industry requirements.
- Design, develop and test both sensing and actuation systems for a cleaning station.
- Development of a prototype system (for an automated cleaning station) and verification of the capability of the system by conducting field experiments.
- Investigation of the feasibility of using low cost 3D RGB-D (such as Microsoft Kinect) sensors for animal measurements such as hump height and horn status.
- Incorporation of 3D RGB-D sensors in the prototype and integration of their outputs in the system overall software design and implementation.
- Investigation of the feasibility of the integration of the inspection data in an overall slaughterhouse operation.
- Investigation of the possibility of the assessment of the animals with the proposed vision system for sex, bruising, cut, and lameness.

4.0 METHODOLOGY

In this section, we provide a description of how the project was conducted, including experimental designs, and results of field tests with the developed prototype.

4.1 Design methodology of the washing system

4.1.1 Cleanliness classification framework and proposed design solutions

As mentioned earlier, our discussions with QA managers during meat processing plant visits confirmed that the cleanliness inspection at the pre-slaughter stage is a *classification problem* in which the inspected animal is visually classified into different classes of cleanliness by humans. To automate the cleanliness inspection and targeted washing tasks in one location, we first devised an image classification framework that enables classification of different sections of animal hide into clean and dirty categories.

Figure 2 shows our proposed cleanliness classification framework: A region of Interest (ROI) is first selected from the animal image. The selected ROI is then partitioned into separate sections (4 sections in this example). Each section is then analysed by a deep-learning-based image classification (see appendix 9.1) algorithm to automatically determine its cleanliness status (clean, dirty, and dagged) from the texture information of the animal skin. Once a specific area is identified as the ROI, targeted washing of that area would commence, which includes targeted washing of the dirty sections only.

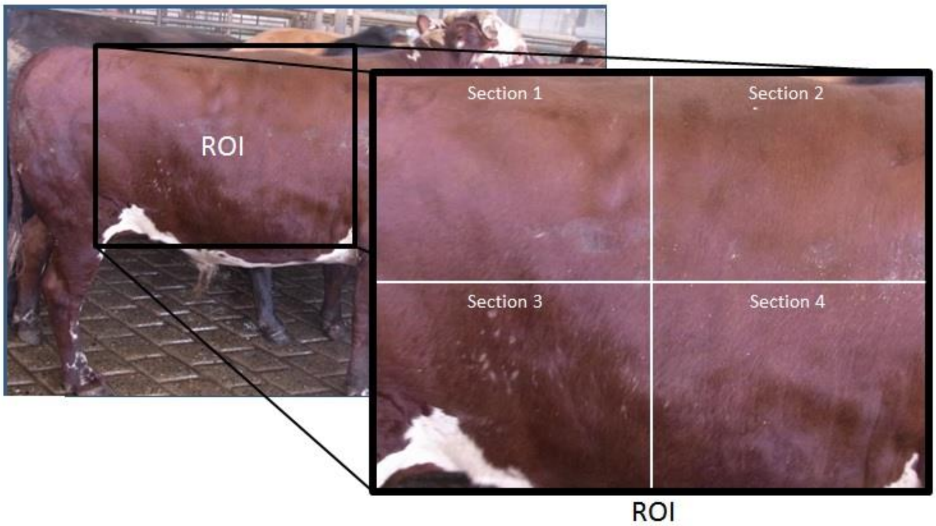


Figure 2. Proposed cleanliness classification framework.

To implement an automated targeted washing system based on realizing the above-mentioned framework, three different solutions were analysed and evaluated. The main goal in the design of the washing system was to develop a mechanism to enable efficient spraying of water to the sections that are determined as dirty by the image classification algorithm.

In the selection of the final design, the cost of the prototype, stress level of the cattle, the likely quality of the washing and the ability to implement the design in a larger scale were taken into consideration. The design also needed to be flexible to allow easy adaptation by various abattoirs as well as providing a method for accommodating the optimal positions of the washing parts.

We first considered a design solution that included the incorporation of a pan/tilt system shown in Figure 3. This design was to be manufactured as a module and placed in the required locations around the race. However, this design had to be rejected as unfeasible due to the difficulties associated with adjusting a nozzle in two different angles. A ball joint was required to offset the force of the nozzle pressure. The torque required to manoeuvre existing ball joints was in excess of 50 N.m in both the x and y direction. This ensured that the designed system required large servos and gearboxes that quickly drove the cost of this design into unfeasible amounts. Off-the-shelf pan tilt systems were also investigated but were also found to be too expensive with the total cost of the design exceeding $12,000.

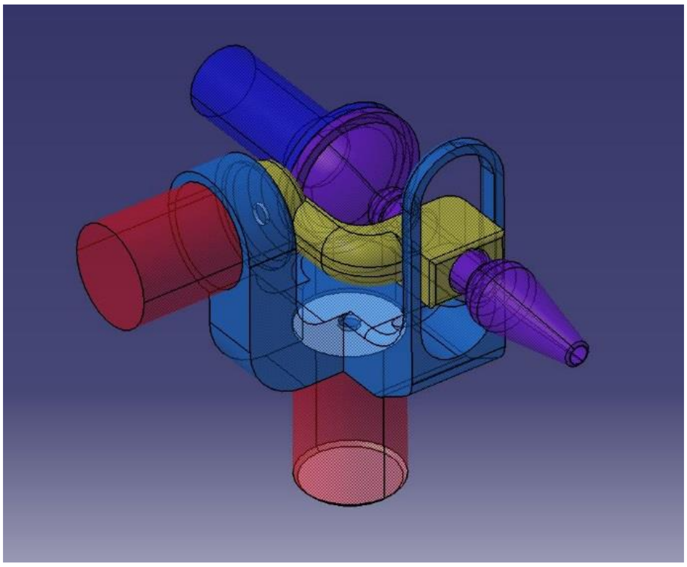


Figure 3. CAD Design of the Pan/Tilt System (first rejected design).

A second design under consideration is shown in Figure 4. This design consists of two racks of four nozzles that are installed on either side of the race. These nozzles are actuated parallel to the cattle by linear belt driven actuators. The flow of the water is controlled by solenoid valves installed with each set of nozzles. The location of the washing required is transmitted to the system from the image classification algorithm that detects the visible contamination (dirty sections).

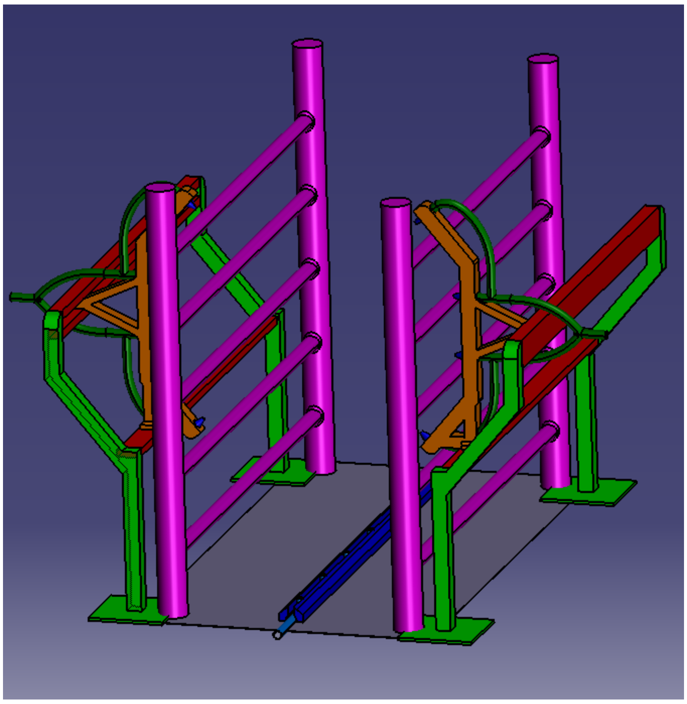


Figure 4. CAD Design of the Linear Belt Driven System (second rejected design).

In order to reduce the amount of force required to move these nozzle racks, they are supported by linear bearings. Another method employed to reduce the force is to disallow the flow of water while the rack is being actuated. This movement system can allow for 1500 mm of motion on either side and can travel this distance in approximately 3 seconds.

A schematic diagram of the control system for this design is shown in Figure 5. The proposed servo motors were Delta ECMA low inertia series rated at 400W, with their technical specifications presented in Appendix 9.2. The servo drivers shown are Delta ASDA-B2, with more information given in Appendix 9.2.

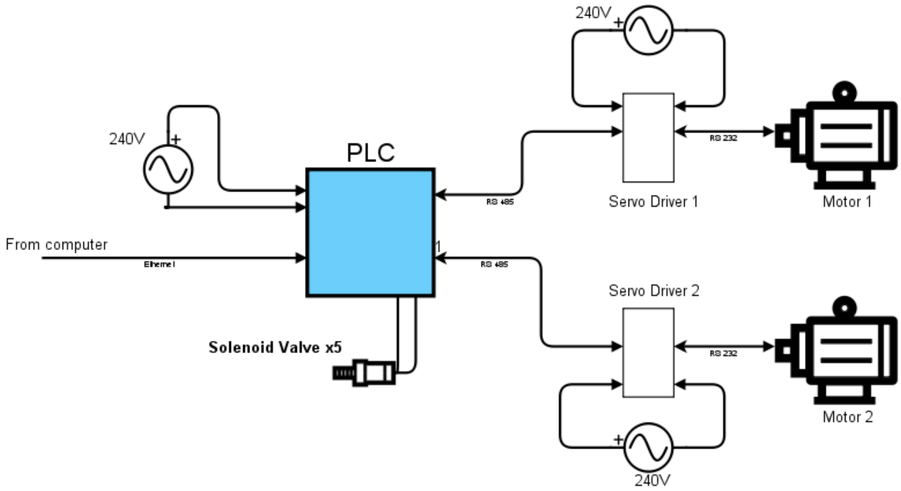


Figure 5. Schematic of linear bet drive control system.

The third (final design), as shown in Figure 6, consists of a fixed matrix of nozzles fitted to the rails on either side of the cattle. Each matrix contains 4 rows of 6 nozzles. This decreases the time required to wash a single cow as there is no delay in the nozzle movement. However, this system requires a more powerful pump as the complexity of this water network creates a lower pressure arriving at the nozzles.

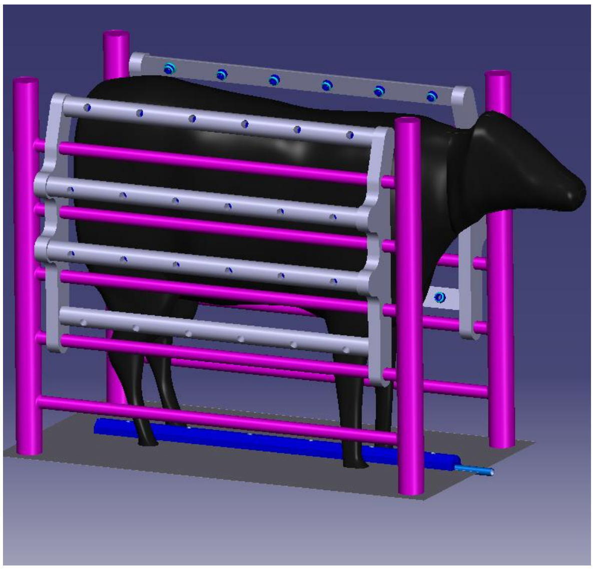


Figure 6. CAD design of the Fixed Array (final design concept).

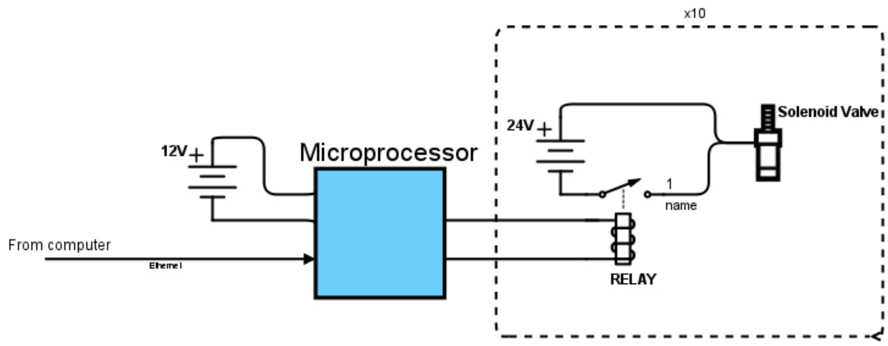


Figure 7. Schematic diagram of the fixed nozzle array control system.

The control system of the third (final) design is simpler and less costly compared to the second (linear belt drive) design, due to the lack of components needing complex control. As shown in Figure 7, the use of relay switches is needed in order to control the solenoid valves, as the output voltage from the board is not sufficient to activate the solenoids.

The underside of animals (particularly around the cutting line) contains the most critical areas for washing. Hence, the decision was made to wash this location on every cow that passes through the system. This is achieved through using an array of stationary nozzles located on the floor of the race, which includes six nozzles underneath the cow (see Figure 8).

Figure 8. CAD design of the race and underside washing.

The positions of nozzles in the final (Fixed Array) design were calculated such that the entire coverage of cattle can be provided. To this end, a literature review was conducted to find the standard size of cattle. A study performed by Bene et al. (2007) looked into dimensions of nine common breeds of beef cows. The results of this study are shown in Table 3. The data provided by this study had limitations due to the exclusion of dairy cattle. Dairy cattle are generally larger than other breeds, so the dimensions obtained are slightly skewed. The distance between the ground and underbelly is critical because the cutting lines are located along the underbelly, and these are the most important areas to wash. A person with experience in the field, Mr Ian Holloway, was consulted in order to find this data. A rough estimate of 60cm was given. Using this data, the number of nozzles needed and their location have been calculated depending on the range of motion and size of water stream provided by the nozzles. The proposed design utilises a line of 6 nozzles that run beneath the legs of the cow, to ensure that the cutting lines are washed.

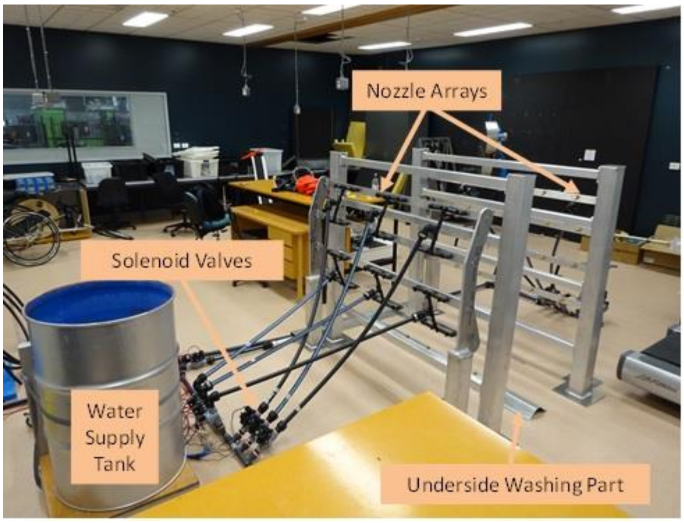
Table 3. Average dimensions of beef cows (Bene et al., 2007)

Measurement	Length (cm)
Height at Withers	134.8
Height at Rump	138.3
Length of Body	140.5
Length of Rump	43.6
Width of Shoulders	46.5
Width of Haunch	55
Width of Sitterbulbs	20.4

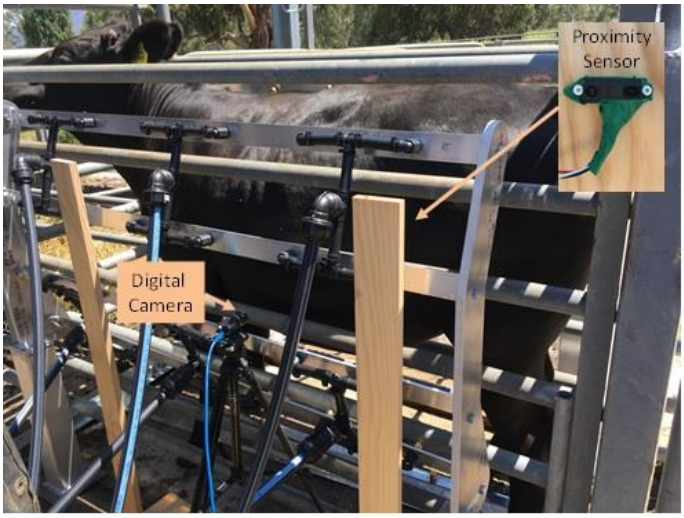
To design the control system for the washing station, the mechanical system and a suitable water network were first designed. The types of actuators used, such as solenoid water valves and servo motors, and the numbers needed were noted. The electronics of the design, such as signal types and voltage levels were investigated, based on which suitable controller devices were researched. Both microcontrollers and programmable logic controllers (PLC) were investigated for their ability to provide the required levels of control. Factors such as number of input and output pins, voltage levels and signal types were the primary considerations taken into account for assessment of suitability of control device candidates. Also, as the cleaning station is to be used at different site locations, the design should make it possible for its electronics to be powered by 240V at 50Hz mains supply. The basic function of the control system is to receive a set of coordinates from the computer-vision system, and then to control the actuators in order to wash the designated areas. In the prototype system, the coordinates from the vision system are transmitted via an Arduino microcontroller.

4.1.2 Developed prototype of the cleanliness inspection/washing system

Figure 9 shows the developed and manufactured prototype of the automated cattle washing system. The prototype includes two infrared proximity sensors, two side washing nozzle arrays, an underside washing part, a water supply system (including a water supply tank, an electric pump and flexible pipes), 13 solenoid valves, electrical and control systems (see Figure 13) as well as a computer vision system (cameras and a computer) to detect contamination. The vision system activates when both proximity sensors detect the cattle, which ensures that the animal is located in the cameras' field of view, and results in capturing images of the cattle hide by cameras. The captured images are then analysed by an image classification algorithm to detect dirty sections on the cattle hide. The coordinates of dirty sections are then sent to the washing system's controller to perform a targeted washing of the animal.



(a)



(b)

Figure 9. Manufactured prototype of the automated cattle washing station (a) excluding camera and proximity sensors in the RMIT laboratory (b) including the camera and proximity sensors at the test sight.

In the developed prototype, both side of the cattle are washed using two arrays of nozzles (see Figure 10). Each array consists of 4 rows of nozzles, and each row consists of 6 nozzles. The nozzles are held in position by a series of aluminium parts manufactured by the RMIT technicians. In order to provide a targeted washing of cattle, an image classification algorithm that determines the animal hide sections that contain contamination is also developed. Each side of the cow is divided into multiple sections (e.g. four quadrants) that are inspected by the image classification system individually and classified into dirty or clean categories. The sections that are identified as clean by the image classification software do not require washing. However, sections that are identified as dirty are washed by activation of specific solenoid valve(s) that direct the water flow from the water reservoir to the nozzles associated with dirty sections.

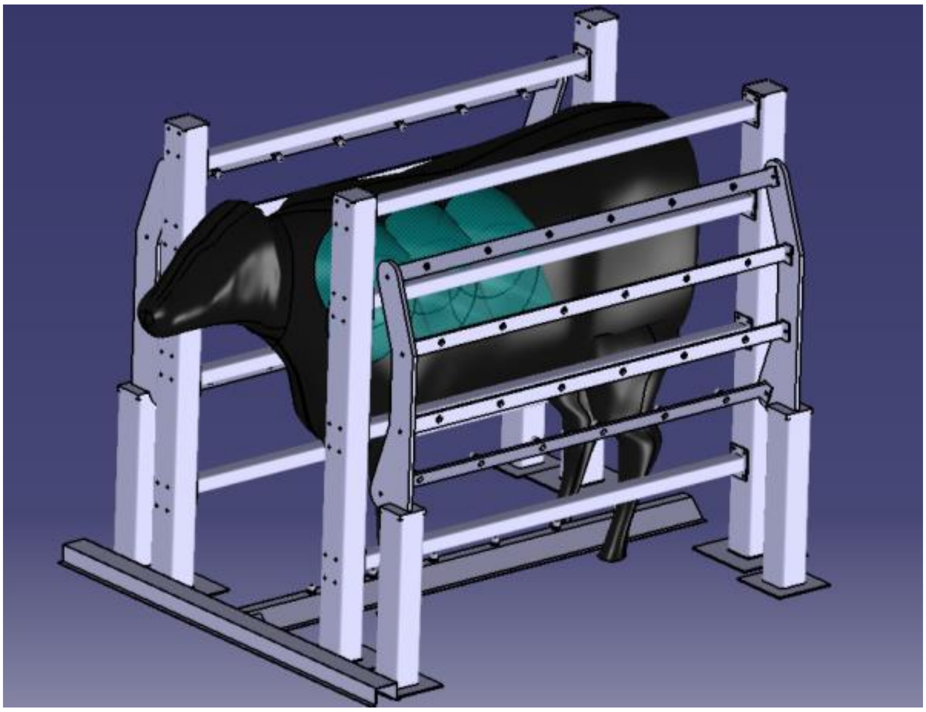


Figure 10. Two arrays of nozzles to perform side washing: each array consists of 4 rows of nozzles, and each row consists of 6 nozzles.

The underside washing part includes an array of 6 stationary nozzles located on the floor of the race, as shown in Figure 11. The cattle move into position over these nozzles before a solenoid valve controls the flow to these nozzles. The plumbing for these nozzles is protected by 2.5mm galvanised steel folded into a desired shape as shown in Figure 11. The 45 degree slopes on the side of the protective channel are designed to reduce the likelihood of cattle stepping on this piece.

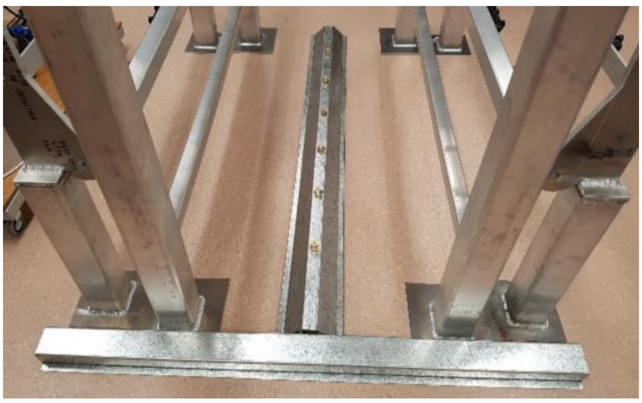


Figure 11. The manufactured underside washing.

Due to the design requirement of creating a portable prototype system, a standalone water supply system was designed and constructed. The water supply system is fixed to a custom low platform supported by caster wheels. This allows the system to be easily moved around any demonstration site. In order to supply the design water requirements of 70L/min and 7 bars, a pump (Lowara e-HM 5hms09 pf1622p) was sourced. The pump (a 9-stage electric pump) is fixed to the platform during operation, as shown in Figure 12. The pump draws water from a 200 litre tank, attached to the platform.

Figure 12. Water supply system assembly.

The pump outputs the water at the increased pressure through a PresFlo control unit. The control unit shuts off the pump if flow is not required or there is no water being supplied from the pump. This protects the pump and the piping network from conditions outside of the design parameters. The controller outputs the water through a BSP 25mm joint. The water is transferred from here to the two solenoid manifolds through 32mm PE100 Poly Pipe, which are located on either side of the system. The step up from the 25mm to the 32mm joint reduces the pressure loss in this part of the line as the water velocity is significantly lower. The pipe is stepped back down to 25mm at the solenoid manifold.

The solenoid manifold on each side contains 6 solenoids. Each solenoid supplies water to 4 of the nozzles. Using multiple solenoids at once can decrease the supply pressure to the nozzles, but the supplied flow remains within the design parameters. The transfer of the fluid for the side that is opposite to the pump takes place through a 32mm pipe to the front of the system under a folded steel channel. The water supply for the underside washing is also transferred through this channel. From the solenoid valves the water is transferred in 25mm PE100 Poly Pipe to the level of the nozzles where it is stepped down to 19mm pipe and split to the nozzles.

The electrical components required for controlling the solenoid valves (see Figure 13), include an Arduino Mega controller, two Arduino-compatible relay boards, a 24 VAC power supply, and an emergency shutdown button. The image classification system can be considered as an external component of the electrical and control system that communicates with the Arduino Mega controller through the the USB port of the computer, and provides the controller with the coordinates of dirty sections of the animal hide. Based on these coordinates, the controller issues activation commands to relays associated with dirty sections. The relays will then provide a 24 VAC signal to specific solenoid valves associated with dirty sections, which results in water being sprayed on dirty sections for a fixed duration. An emergency shutdown button is also added to the system to enable quick termination of the washing procedure if signs of discomfort (e.g. stress, vocalizing, aversion, etc.) are observed in the animal that is being washed.

Figure 13. Electrical and control systems.

4.1.3 Field experiments

To ensure animal welfare requirements are being met throughout the field experiments, we first submitted an animal ethics application to RMIT University's Animal Ethics Committee (AEC), and obtained the required animal ethics approval. Although the automated cattle washing station is designed and built with its own race, for testing purposes, it has to be fitted into the existing raceway of farm where we tested the prototype with live animals. We successfully tested the performance of the prototype, and results of the field experiments showed the capability of the system in significantly reducing the visible dirt on the animal skin.

Our design for the field experiment is as follows. After selecting an animal, the cleanliness status of the animal is recorded before and after the washing procedure to enable verification of the prototype's washing capability. The efficacy of the cleaning is visually evaluated by ranking the cleanliness status of the animal. The automatic washing procedure is carried out by detection of dirty sections on animal hide using the computer vision system, and spraying water on sections that are classified as dirty by the image classification software. The animal is imaged once when it is located in the space between the two nozzle matrixes (shown in Figure 9). An image classification software analyses the images taken from both sides of the animal and detects dirty sections of the animal hide. Based on the cleanliness status of every section of the animal hide, the controller issues activation commands to different solenoid valves. Each nozzle is connected to a solenoid valve through flexible plastic pipes that direct water to the nozzle. The solenoid valves are by default closed, and this stops the flow of water from the nozzles during the operation. If a section of the animal hide is identified as dirty, the valve associated with that section is activated by the controller for a set period of time (maximum one minute). However, if a section of the animal hide is identified as clean, water is not sprayed from the nozzle that is designed to target that section to avoid unnecessary overall water spraying.

To ensure that the animal welfare requirements are being met during a typical experiment, experienced animal handlers should constantly monitor the status of the animal under experiment. If the animal that is being washed is stressed or signs of discomfort (e.g. vocalizing, aversion, escaping behaviour) are observed, the washing procedure will immediately be terminated by pushing the emergency shutdown button. This would shut off the entire washing system and in this case, the animal will be withdrawn from the study. We conducted the experiments without any adverse incident, and the animals were returned to their pens unharmed at the end of our experiments.

Figure 14 shows the disassembled components of the prototype. The first step of preparing the prototype for experiments was to assemble different components of the system, and integrate those with the existing race way (see Figure 15) that was available in the farm where experiments were carried out.

Figure 14. Disassembled components of the prototype.

Figure 15. The existing race way that was available in the farm where experiments were carried out.

Figure 16 shows the assembled nozzle arrays on either side of the race way. The next step was to connect the solenoid valves to the electrical and control system, as shown in Figure 17.

(a) (b)

Figure 16. Assembled nozzle arrays on either side of the race way: (a) side A of the race way (b) side B of the race way.

Figure 17. Connecting the solenoid valves to the electrical and control system.

The image of a typical dirty section, before and after the washing procedure is shown in Figure 18. The figure shows that the contaminated area is visually clean after the washing is performed.

(a) (b)

Figure 18. The image of a typical dirty section, (a) before and (b) after the washing procedure is performed.

4.2 Integrated cattle inspection and cleaning station

The integrated cattle inspection and washing station is designed around the implementation of state-of-the-art three-dimensional (3D) vision sensors to measure important physical characteristics of livestock. It is envisaged to integrate four Kinect cameras into the overall cattle inspection and washing station to realise measurement of physical qualities, and potentially detection of signs which may suggest a level of lameness in cattle.

The current methods used for the measurement of livestock's physical attributes in preparation for slaughter require a handler to manually carry out the task. This not only results in a potentially lengthy process, but also requires that handlers be present in the abattoir which can inflict significant mental stress due to them being in a depressing work environment. Additionally, being physically handled in a closed space can induce mental stress within the livestock which has the potential to negatively impact the quality of meat products. As such, we have developed an integrated cattle inspection and washing station, where animals can be measured automatically and electronically, using an array of RGBD cameras. The relevant literature was first reviewed (see report #6), and a systematic approach that enables the incorporation of three-dimensional data to the overall inspection system was proposed. The approach involves the use of four Kinect cameras mounted at different angles, 2 on each side of the animal, having their generated point clouds merged together to construct a 3D representation of the animal. Having access to the reconstructed 3D representation potentially enables measurement of physical characteristics such as hump height and horn status.

It was determined that Kinect cameras would be the most appropriate tools for the job due to the versatility gained by having both an RGB camera and a depth camera. This thereby makes it possible to capture standard, colour images as well as depth images; which can also be represented as a point cloud. This decision was also impacted by them being relatively cheap in comparison to similarly performing cameras and set ups.

A setup was devised that would allow the Kinect cameras to have a full view of the cattle passing through, both vertically and horizontally. It was determined that four Kinect cameras should be adequate to achieve this. The field of view of the cameras meant that they needed to be placed quite far back in order to capture a complete image of the cow horizontally. An angle of 70° needed to be formed between the two raceways to allow this. To minimise the cameras' fields of view being obstructed, it was determined that a wire guide will be used in place of solid bars, while still having the outer raceway being as solid as possible in the case of the livestock becoming frightened and trying to escape. These considerations led to the devising of the setup shown in Figure 19 and Figure 20.

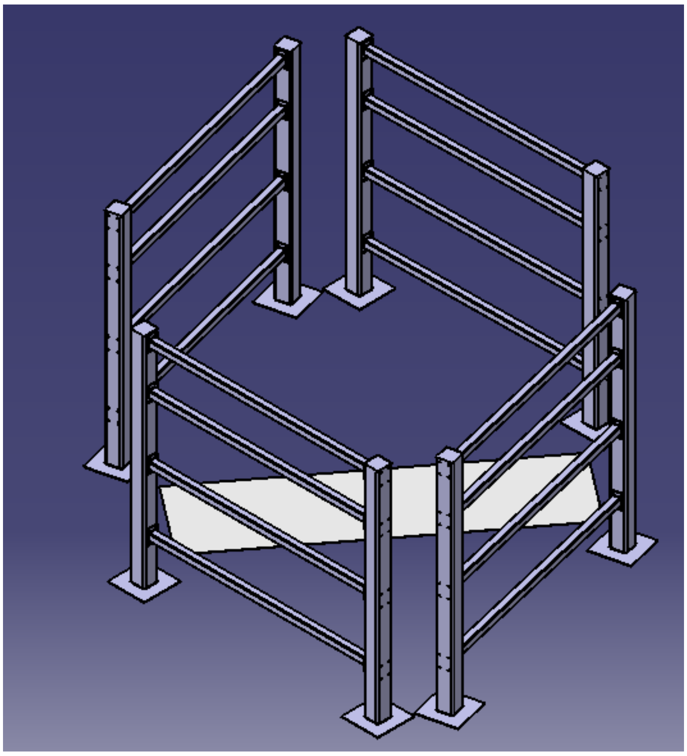


Figure 19. Isometric view of the proposed system to carry out 3D measurements.

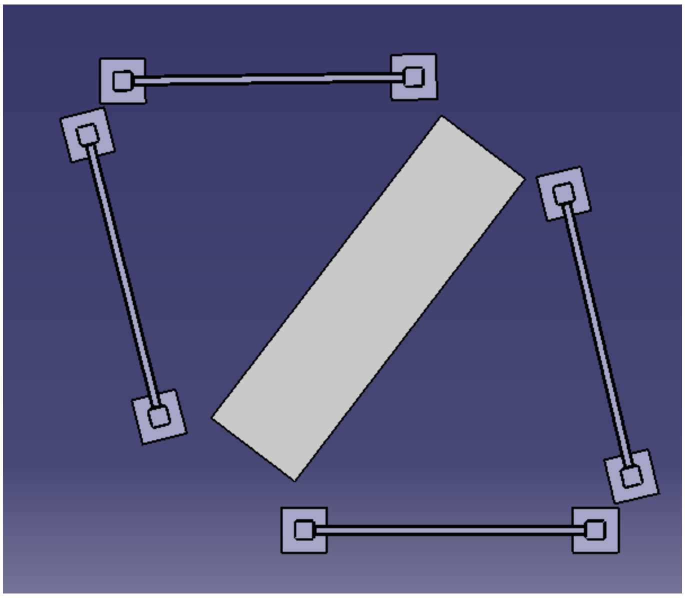


Figure 20. Top down view of the proposed system to carry out 3D measurements.

The two Kinect cameras of each side are mounted to one of the central poles on each side (see Figure 21), one above the cow and one below the cow on each side. The Kinects on each side are separated by 1.6 metres vertically and there is 3.32 metres between the Kinects across the raceway. Each Kinect is angled at approximately 30 degrees towards the cow such that the fields of view cover the entirety of the animal with some overlap, allowing the creation of a 3D reconstruction using point cloud data generated from the Kinects.

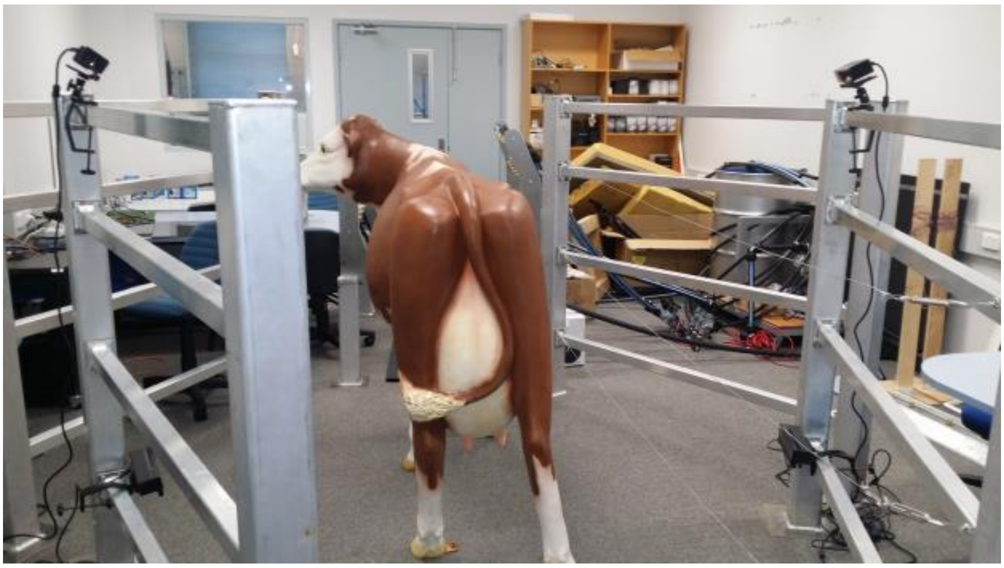


Figure 21. The manufactured prototype of the proposed system to carry out 3D measurements.

The data were streamed from Kinect cameras directly into the Matlab software, and processing of the captured point clouds included rotations and translations that depend on the distinct Kinect and the combining of a point cloud data set from each Kinect. The post-processing of data included noise reduction/removal which ensures that final reconstructions are more accurate.

A cow model (see Figure 21) was acquired to assist with the testing. Point clouds were collected from four separate views, and then orientated/aligned using transformation matrices. The initial merged point cloud contains unnecessary background information (Figure 22). Result of the final merged Point Cloud after removal of the background information is shown in Figure 23. The final result (see Appendix 9.3 for more sample merged data) is a fully three-dimensional, rotatable point cloud from which the desired measurements can be taken.

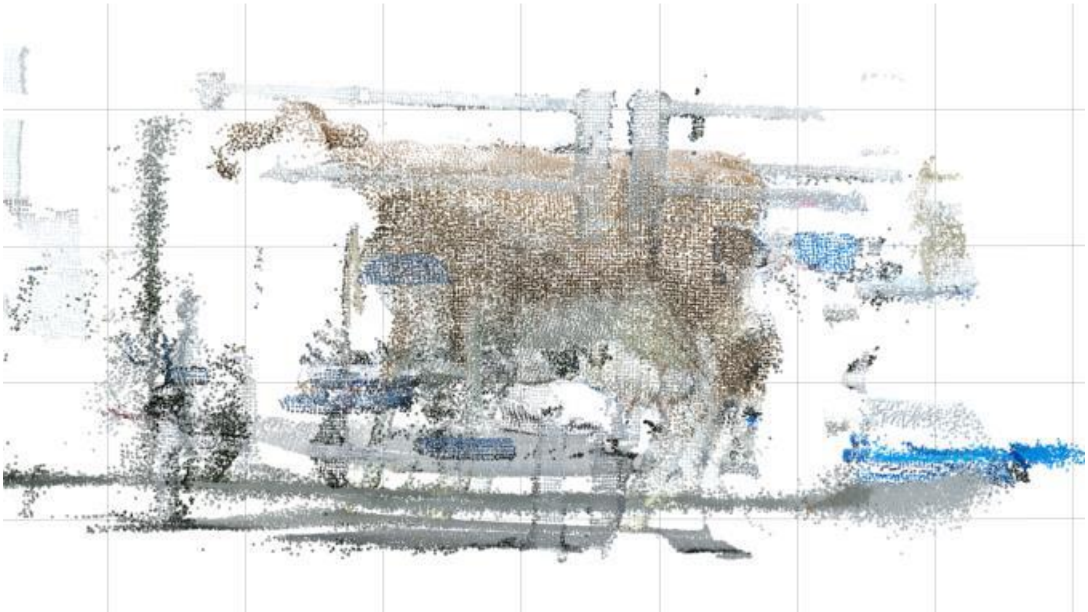


Figure 22. A sample of Point Cloud with background information.

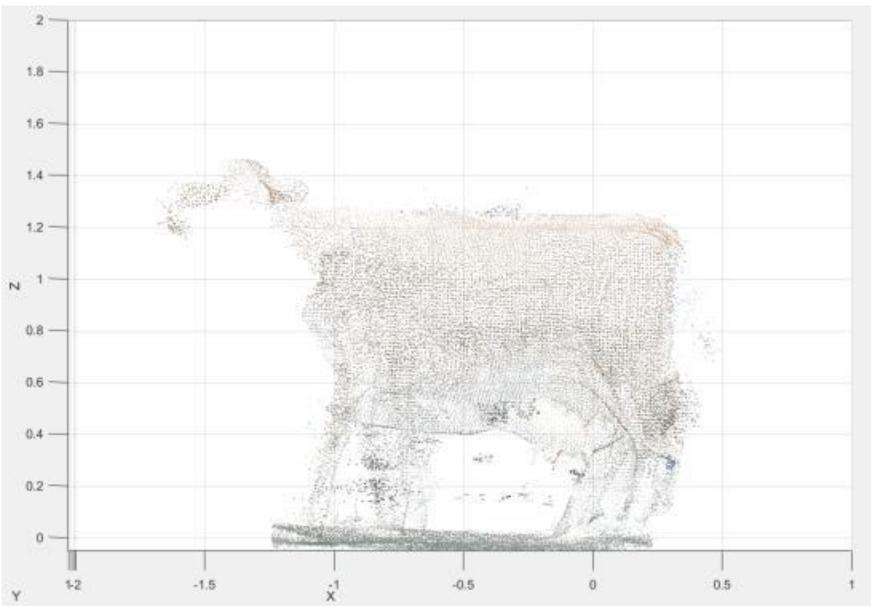


Figure 23. A sample of final merged Point Cloud.

5.0 PROJECT OUTCOMES

The major outputs of this project are threefold:

- // Effective automated visual inspection technology, specifically developed for live animal inspection applications in the Australian red meat processing industry: the technology not only entails the computer science behind the methodologies developed for processing the images and arriving at detection and classification results, but also the devising and integration of the hardware and software in practice.
- // Flexible yet efficient automated cleaning technology, specifically developed for working in tandem with the above mentioned automated inspection technology, for cleansing the animals off their possible faecal contamination and external hygiene of hides. This technology needs to be able to rapidly communicate with the inspection outcomes and lead to decision of cleaning/marking of the animals in real-time and with a high throughput. It also has to be sufficiently flexible to be tailored to the specific Australian environmental and climate conditions and logistic and operational constraints of the end-user industries.
- // A complete working prototype for automated inspection and cleaning of livestock before slaughter: This outcome provides the main drive for the industries to embrace the new technology by seeing an actual example of how the animals are inspected then cleaned/marked in a fast rate.

6.0 DISCUSSION

There were two prominent methods of data acquisition/processing used throughout this project. The first was accomplished through the use of RGB cameras and well-established image processing techniques, while the second method relies more on depth information provided by Kinect cameras through the use of point clouds. Common RGB digital cameras were used in this project to assess the cleanliness status of cattle. An extensive image database of dirty/clean cattle were used in the implementation of deep learning techniques, which are the state-of-the-art in machine learning, for the required task of the cleanliness classification task in this project. Textural signatures available in the RGB images enabled highly accurate image classifications through training deep learning networks. The RGB images appear to be a more reliable source of information compared to thermal images captured by IR cameras, because several factors (e.g. cattle being wet at the pre-slaughter stage) affect the thermal imaging process.

The use of multiple Kinect cameras results in multiple point clouds which can then be aligned in such a way as to represent a subject, in this case cattle, as a 3D reconstruction. There are a number of programs that can assist with this reconstruction, however due to accessibility, Matlab is the one that was chosen to perform this task. This is further validated by its ease of use and built in Kinect modules. Therefore, the data can be streamed from the Kinect directly into Matlab to be processed, which will consist of a rotation and translation that will depend on the distinct Kinect and the combining of a point cloud data set from each Kinect; these will then be cleaned up to reduce noise, leading to more complete reconstructions. The reconstructed images potentially enable determination of a selected physical characteristic by determining distances between specific points.

7.0 CONCLUSIONS/RECOMMENDATIONS

Different design solutions were considered for the development of an automated cattle cleanliness inspection and washing system. The proposed Fixed Array design provides a number of advantages compared to the Linear Belt Driven design. The system is estimated to cost less and contain less complexity. The moving parts in the linear belt driven system also have the capacity to startle or alarm cattle (i.e. induce stress). As such, the developed prototype based on the Fixed Array design provided a number of advantages including minimisation of stress on cattle during washing, potential reduction of water consumption, more consistent level of animal treatment, savings in labour costs, and improving the hygiene of red meat products by significantly reducing the amount of visible contamination on cattle hide. The capability of the system to automatically detect and wash dirty sections of the animal hide was verified by field experiments.

Significant attempts have been made worldwide to implement some form of integrated system in agricultural fields, in particular those pertaining to livestock. However, it was only after the rise of RGB-D technology and the accessibility of the successful Microsoft Kinect that expedited growth within the field. With the help of relatively cheap RGB-D cameras that also provide depth information, it has become possible to integrate a multitude of measurements in a single integrated system. The proposed integrated measurement system in this report is recommended to provide an opportunity to assess important characteristics of livestock in tandem with the developed cattle cleanliness inspection and washing system. This potentially enables measurement of physical attributes of cattle, leading to improved record keeping capability at the pre-slaughter stage.

8.0 BIBLIOGRAPHY

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9.0 APPENDICES

9.1. Deep-learning-based image classification

The aim of the image classification task in this project is to classify images of different sections of cattle hide into different classes of cleanliness using deep learning techniques. Convolutional Neural Network (CNN) is a well-known category of deep learning that is reported to produce promising results in different object recognition tasks. Its architecture is indeed well suited to object classification through learning complex features.

Deep CNNs work based on consecutively extracting features from input images in multiple layers. The first layer of a typical CNN is associated with low-level features (e.g. edges, corners, etc.), and subsequent layers deal with higher level features such as shapes or objects. The last fully connected layer performs the classification by using previous features as its input. Figure 24 shows the architecture of a typical CNN. A CNN typically consists of 3 types of layers: convolutional, pooling, and fully connected layers.

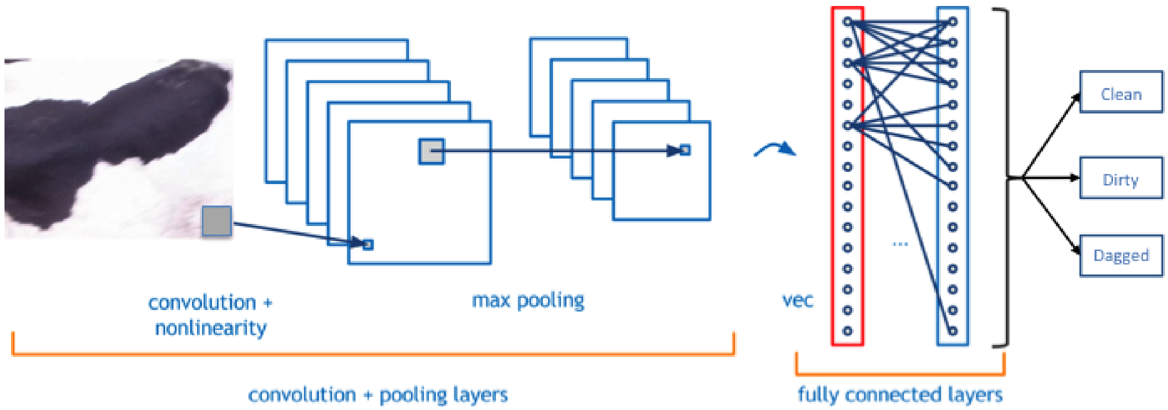


Figure 24. A typical convolutional neural network architecture.

Convolution is a mathematical operation that can be interpreted as applying a filter to a given image. The filter is a matrix that consists of a set of weights. Convolutional layers include convolving images with some filters. The convolution operation is carried out by sweeping a filter over the image from the top left corner to the bottom right corner. At each position, the weighted sum of the pixels is calculated as

$$\omega^T \times x + b,$$

where the ω^T is the weight matrix associated with the filter, x is the input vector and b is the bias vector. Filter weights are the parameters that can be learned with a back-propagation algorithm. The purpose of the back-propagation algorithm is to update the weights of the network in order to reduce the error of the network.

The summary of a convolutional layer is as follows:

- Input size: W1 x H1 x D1
- Hyper-parameters: K: #filters, F: filter size (FxF), S: stride, P: amount of padding,

- Output size: W2 x H2 x D2
- #parameters = (F.F.D).K + K
  - F.F.D : Number of parameters for each filter (analogous to volume of the cuboid)
  - (F.F.D).K : Volume of each filter multiplied by the number of filters
  - +K: adding K parameters for the bias term

Some additional points to be taken into consideration:

- K should be set as powers of 2 for computational efficiency,
- F is generally taken as an odd number,
- F=1 might sometimes be used and it makes sense because there is a depth component involved.

Pooling is a procedure that takes inputs over a certain area and reduces that to a single value (downsampling). This provides invariance to rotations and translations for object recognition. The last layer is a fully connected layer in which each pixel is considered as a separate neuron just like a regular neural network.

<u>AlexNet</u>

AlexNet was the winning deep learning solution for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012. The AlexNet consists of 11 layers with the architecture shown in Figure 25. Note that the output of each layer will be the input of the next layer.

- Layer 0: Input image
  - Size: 227×227×3
- Layer 1: Convolution with 96 filters, size 11×11, stride 4, padding 0
  - Size: 55 x 55 x 96
  - (227-11)/4 + 1 = 55 is the size of the outcome
  - 96 depth which means 96 filters
- Layer 2: Max-Pooling with 3×3 filter, stride 2
  - Size: 27×27×96
  - (55 – 3)/2 + 1 = 27 is size of outcome
  - depth is same as before, i.e. 96 because pooling is done independently on each layer
- Layer 3: Convolution with 256 filters, size 5×5, stride 1, padding 2
  - Size: 27×27×256
  - Because of padding of (5-1)/2=2, the original size is restored
  - 256 depth because of 256 filters
- Layer 4: Max-Pooling with 3×3 filter, stride 2
  - Size: 13×13×256
  - (27 – 3)/2 + 1 = 13 is size of outcome
  - Depth is same as before, i.e. 256 because pooling is done independently on each layer
- Layer 5: Convolution with 384 filters, size 3×3, stride 1, padding 1
  - Size: 13×13×384
  - Because of padding of (3-1)/2=1, the original size is restored
  - 384 depth because of 384 filters
- Layer 6: Convolution with 384 filters, size 3×3, stride 1, padding 1
  - Size: 13×13×384

    - Because of padding of (3-1)/2=1, the original size is restored
    - 384 depth because of 384 filters
- Layer 7: Convolution with 256 filters, size 3×3, stride 1, padding 1
    - Size: 13×13×256
    - Because of padding of (3-1)/2=1, the original size is restored
    - 256 depth because of 256 filters
- Layer 8: Max-Pooling with 3×3 filter, stride 2
    - Size: 6×6×256
    - (13 – 3)/2 + 1 = 6 is size of outcome
    - Depth is same as before, i.e. 256 because pooling is done independently on each layer
- Layer 9: Fully Connected with 4096 neuron
    - In this later, each of the 6×6×256=9216 pixels are fed into each of the 4096 neurons and weights determined by back-propagation.
- Layer 10: Fully Connected with 4096 neuron
    - Similar to layer #9
- Layer 11: Fully Connected with 1000 neurons
    - This is the last layer and has 1000 neurons because IMAGENET database has 1000 classes to be predicted.

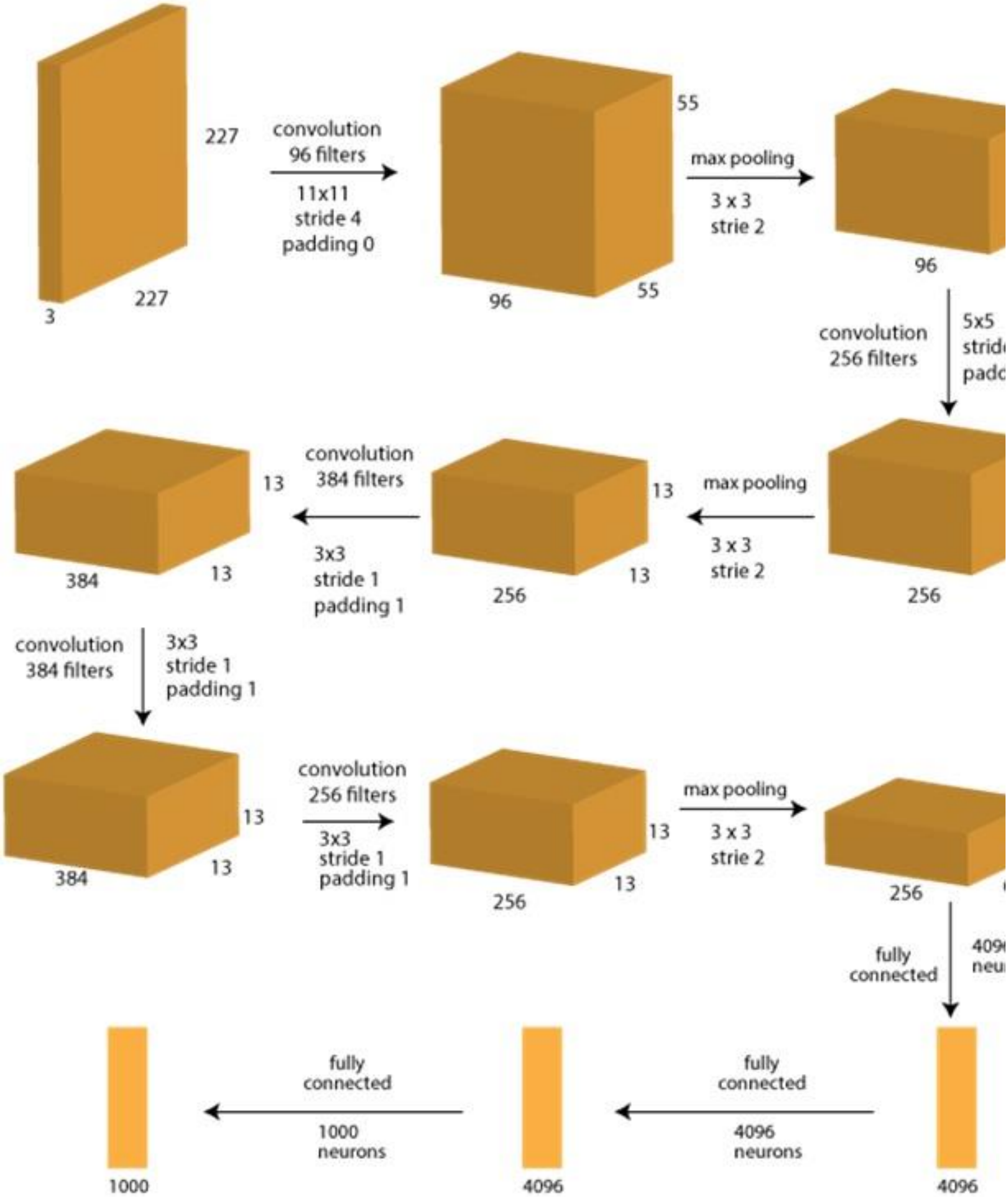


Figure 25. AlexNet architecture

To implement the convolutional neural network for this project, a deep learning framework called Caffe and Digits toolbox was used. Caffe is an open-source deep learning framework, which is developed by Berkeley Vision and Learning Center (BVLC). It has an expressive architecture in which models and optimisations are defined by configuration without hard coding. Models can be trained on either CPU or GPU machines by setting a single flag. The speed of this framework has made it ideal for research experiments and industry deployment. It can process over 60M images per day with a single NVIDIA k40 GPU. There are four steps in training a CNN using Caffe:

1. Data preparation: in this step, we cleaned the images and stored them in a format that can be used by Caffe. We wrote a Python script that will handle both image pre-processing and storage.
2. Model definition: in this step, we chose a CNN architecture and we defined its parameters in a configuration file with extension .prototxt.
3. Solver definition: the solver is responsible for model optimisation. We defined the solver parameters in a configuration file with extension .prototxt.
4. Model training: we trained the model by executing one Caffe command from the terminal. After training the model, we obtained the trained model in a file with extension .caffemodel. After the training phase, we used the .caffemodel trained model to make predictions of new unseen data.

Currently 1493 photos of beef cattle photos have been collected from cattle in slaughterhouses and a cattle texture database consists of 2200 texture patches, which classified into three classes including clean, dagged, and dirty (See Figure 26). The resolutions of the texture patches were different, but depending on the CNN architecture they were resized.

In order to have a proper dataset the following steps have been performed:

5. Run histogram equalisation on all training images. Histogram equalisation is a technique for adjusting the contrast of images.
6. Resize all training images to a 227×227 format.
7. Divide the training data into 3 sets: one for training, one for validation and the other for test. The training set is used to train the model, and the validation set is used to calculate the accuracy of the model.
8. Store the training and validation in 2 LMDB databases. train_lmdb for training the model and validation_lmbd for model evaluation.

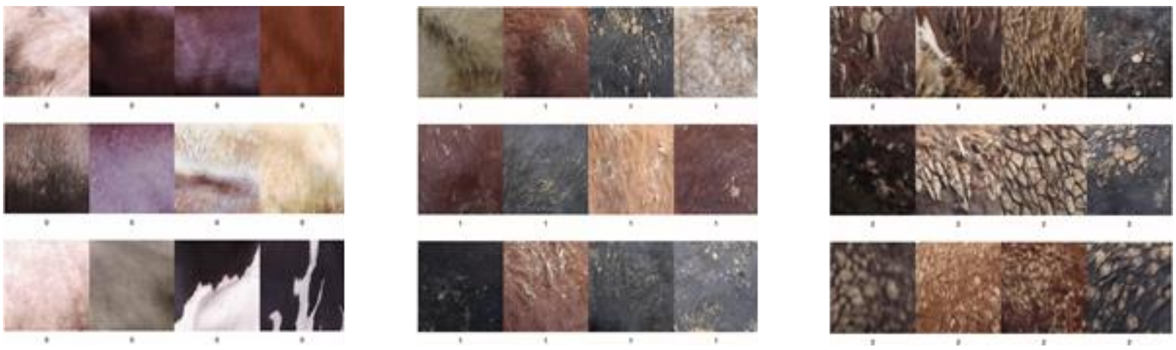


Figure 26. Samples of the prepared dataset. a. Clean dataset denoted by ‘0’. b. Dirty dataset denoted by ‘1’. c. Dagged dataset denoted by ‘2’.

The mean image of training data needs to be generated. Then, the mean image is subtracted from each input image to ensure every feature pixel has zero mean. This is a common pre-processing step in supervised machine learning algorithm.
After deciding on a CNN architecture, its parameters are defined in a .prototxt train_val file. We chose the Alexnet to use as the network architecture, after a careful review of all available architectures.

Solver Definition
The solver is responsible for model optimisation. The solver's parameters are defined in a .prototxt file. The solver computes the accuracy of the model using the validation set in every predefined iteration. There are different strategies for the optimisation process. The following solvers are used in our work.

Stochastic Gradient Descent	Adaptive Gradient	Nesterov's Accelerated Gradient
AdaDelta	Adam	RMSprop

Model Training

After defining the model and the solver, a model can be trained. During the training process the loss and the model accuracy is monitored. Caffe takes a snapshot of the trained model in every predefined iteration, and stores it under caffe_model_1 folder.

Plotting the Learning Curve

A learning curve is a plot of the training and test losses as a function of the number of iterations. These plots are very useful to visualise the train/validation losses and validation accuracy where the accuracy is calculated as follows:

$$accuracy = (1 - \frac{N_{errors}}{N_{samples}}) \times 100$$

Logarithmic loss (or logloss) is a performance metric for evaluating the predictions of probabilities of membership to a given class. The scalar probability between 0 and 1 can be seen as a measure of confidence for a prediction by an algorithm. Predictions that are correct or incorrect are rewarded or punished proportionally to the confidence of the prediction.

The outcomes of our method using multiple solvers for training the defined CNN are listed here. In Table 1 the confusion matrix is calculated. The confusion singular, also known as an error matrix or contingency table, allows us to see if the algorithm systematically assigns wrong labels, by contrasting the net's predictions against a benchmark/ground truth.

AlexNet Using AdaDelta Solver

0	1	2	Class accuracy
8	0	0	100%
4	3	1	37.5%
0	2	2	50.0%

AlexNet Using AdaGrad Solver

0	1	2	Class accuracy
0	0	8	0%
0	0	8	0%
0	0	4	100.0%

AlexNet Using Adam Solver

0	1	2	Class accuracy
0	8	0	0%
0	8	0	100%
0	4	0	0%

AlexNet Using Nag Solver

0	1	2	Class accuracy
7	0	1	87.5%
0	8	0	100%
0	2	2	50.0%

AlexNet Using RMSprop Solver

0	1	2	Class accuracy
0	0	8	0%
0	0	8	0%
0	0	4	100.0%

AlexNet Using SGD Solver

0	1	2	Class accuracy
7	1	0	87.5%
1	6	1	75.0%
0	1	3	75.0%

Table1. Confusion matrices

In order to calculate the overall error in the predictions, the trained model is used to predict the outcomes on data where the real outcome is known. The error on the same data set used to train the model is called the training error (training loss), and the error on an independent sample is called the validation error (validation loss). A model will commonly perform better on the data it was trained on than on an independent sample. The difference between the training error and the validation error reflects overfitting of the model.

Looking at Figure 14 – 19, it is evident that training the model using SGD optimisation method achieved better validation accuracy -- 80%, and it stopped improving after 30 epochs. In addition, based on the confusion matrix, we concluded that the class accuracy of the SGD-based model is more reliable compared to the other models.

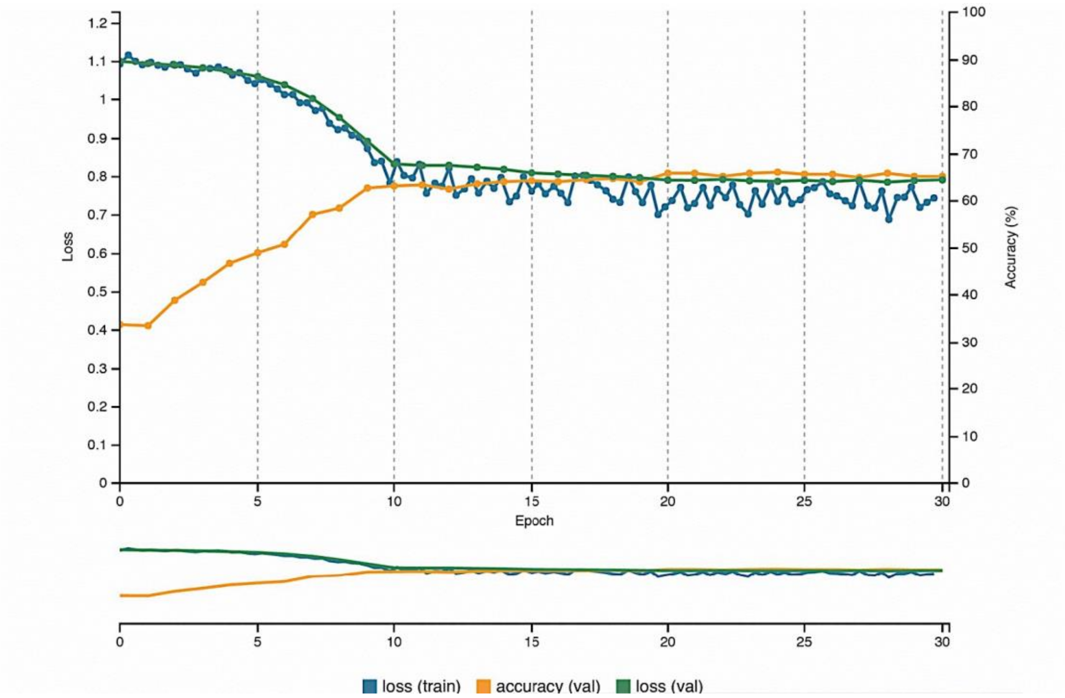


Figure 27. Accuracy and loss curves for AlexNet Using AdaDelta Solver.

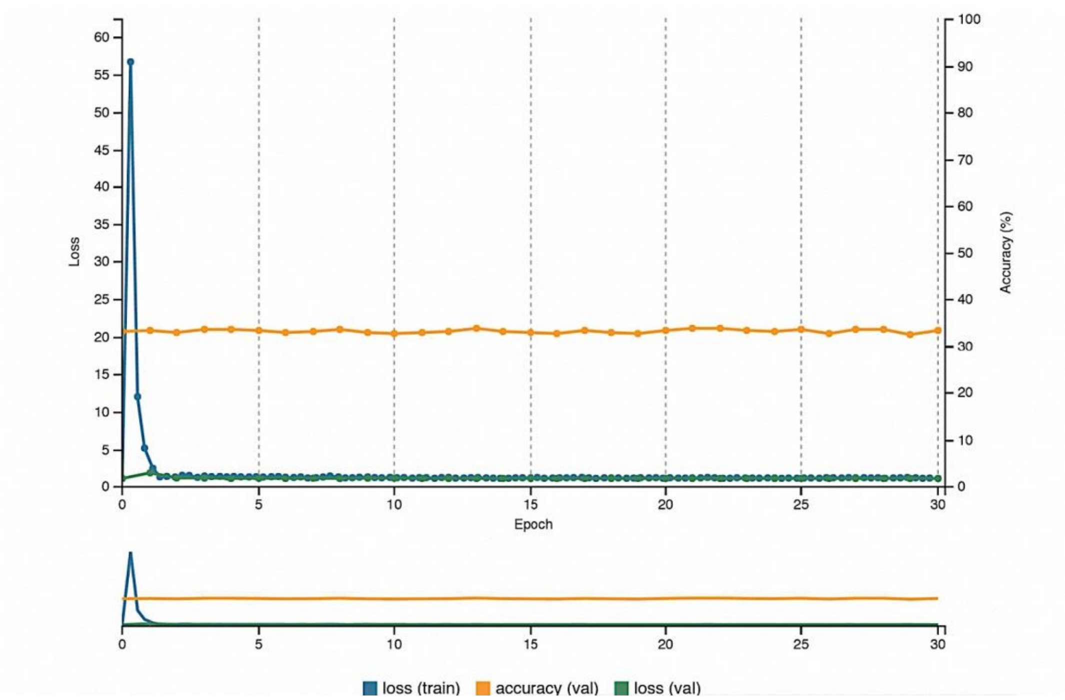


Figure 28. Accuracy and loss curves for AlexNet Using AdaGrad Solver.

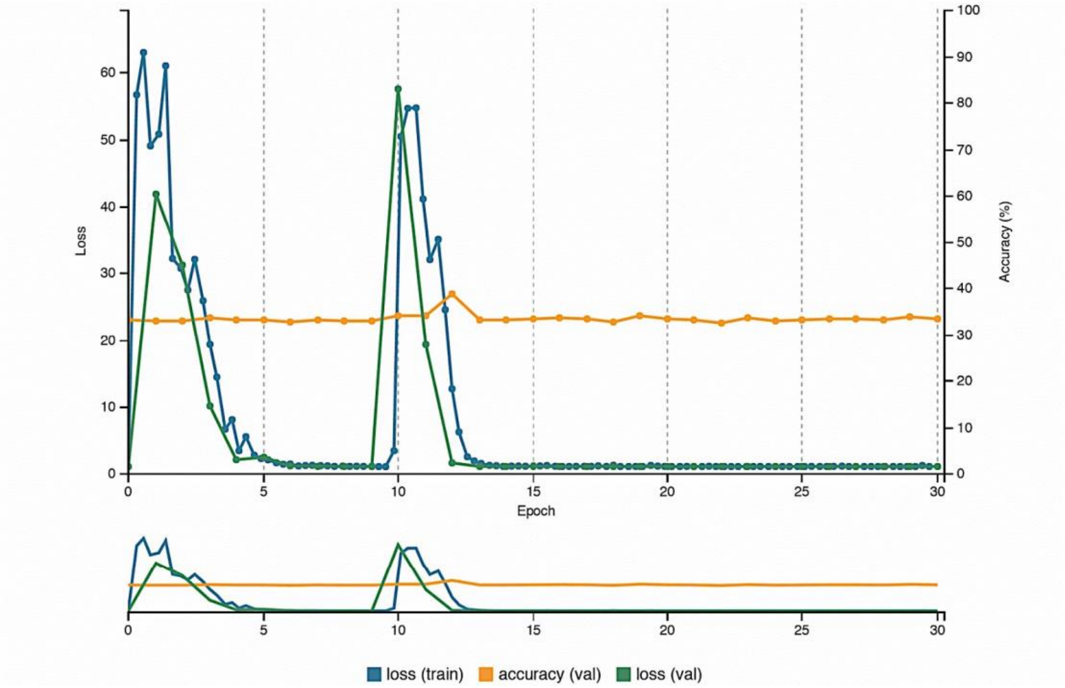


Figure 29. Accuracy and loss curves for AlexNet Using Adam Solver.

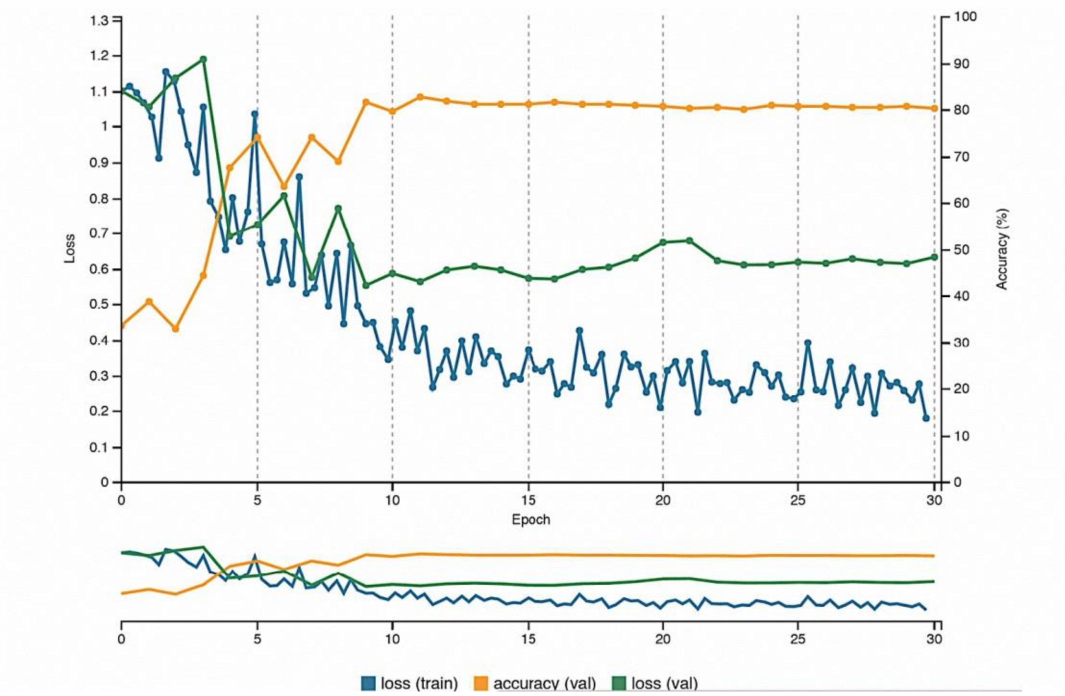


Figure 30. Accuracy and loss curves for AlexNet Using Nag Solver.

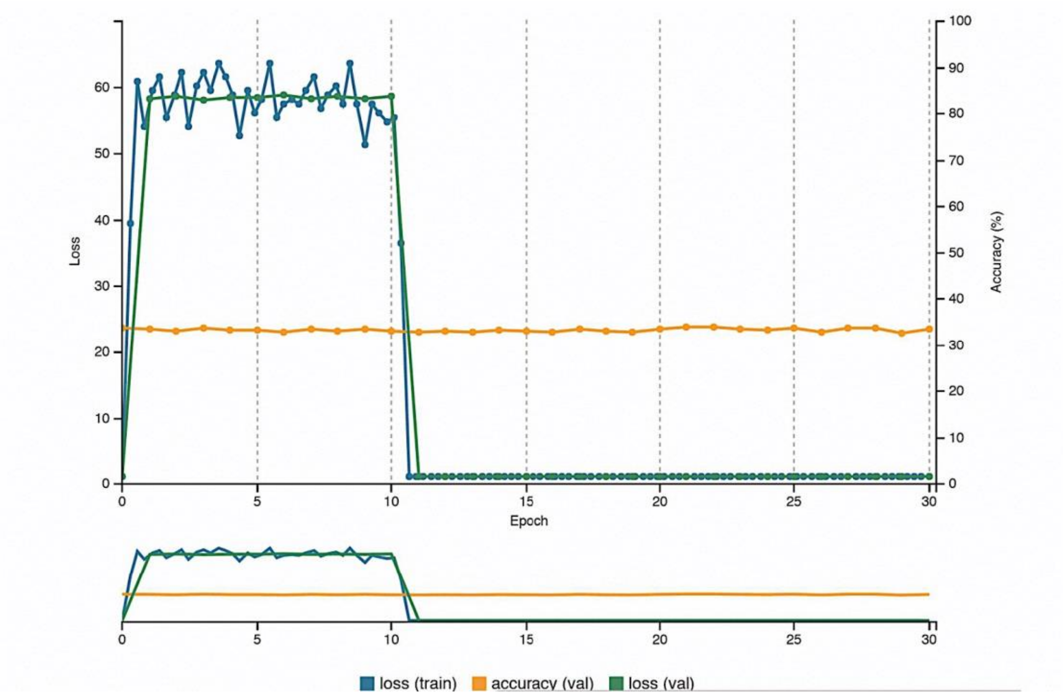


Figure 31. Accuracy and loss curves for AlexNet Using RMSprop Solver.

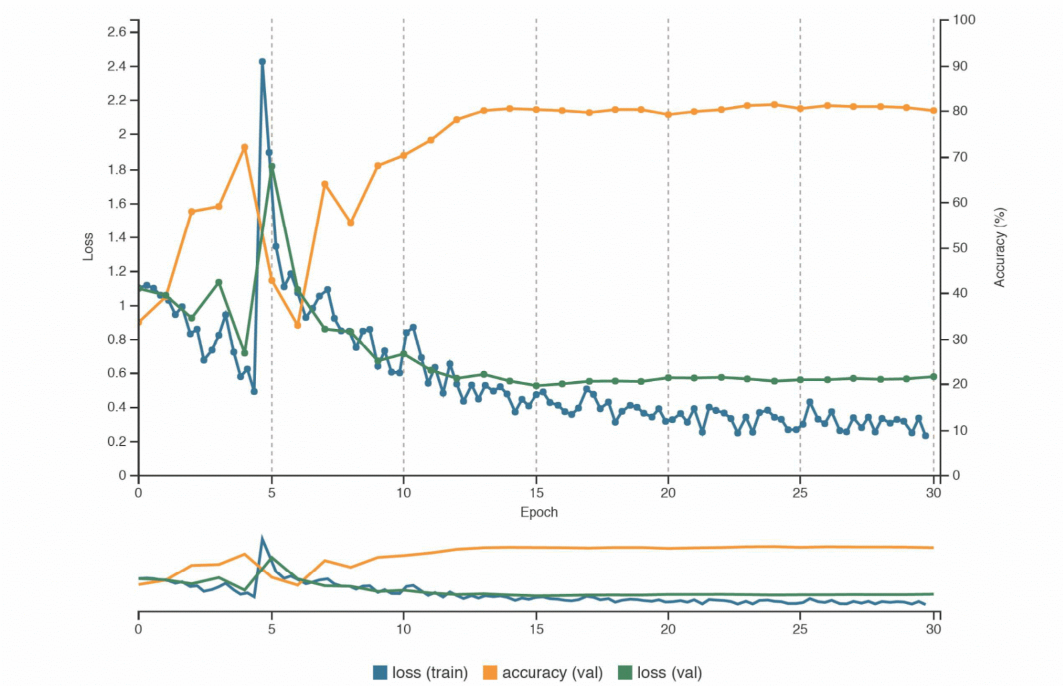
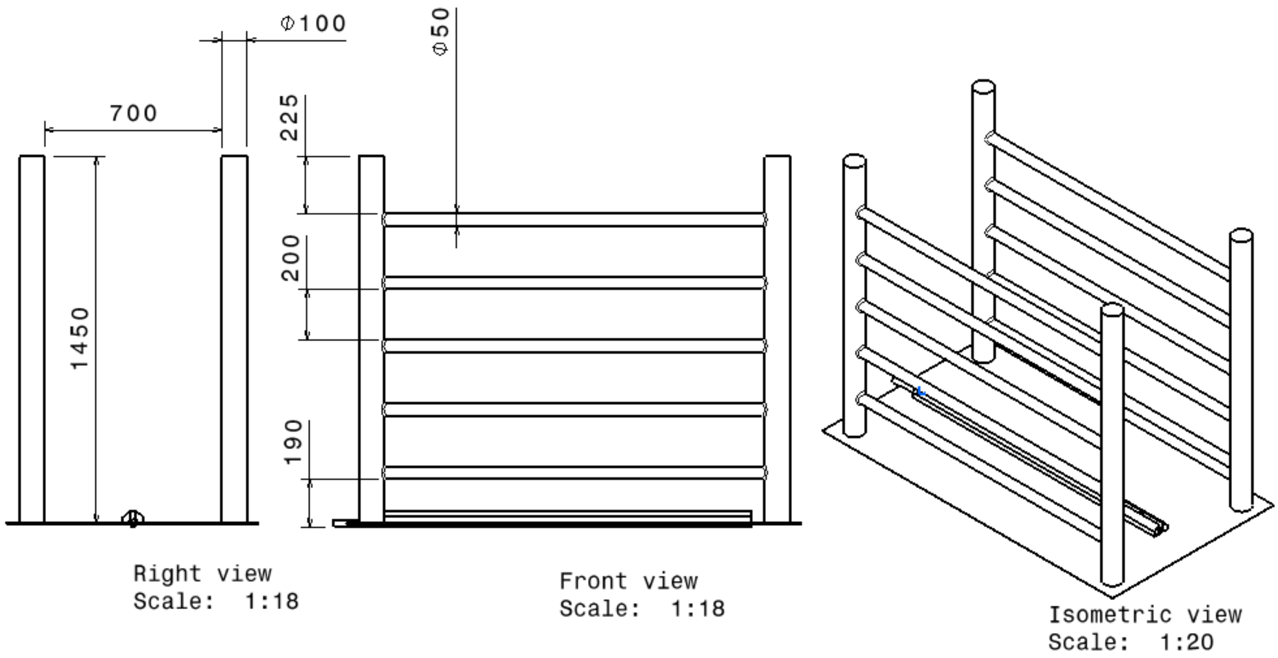


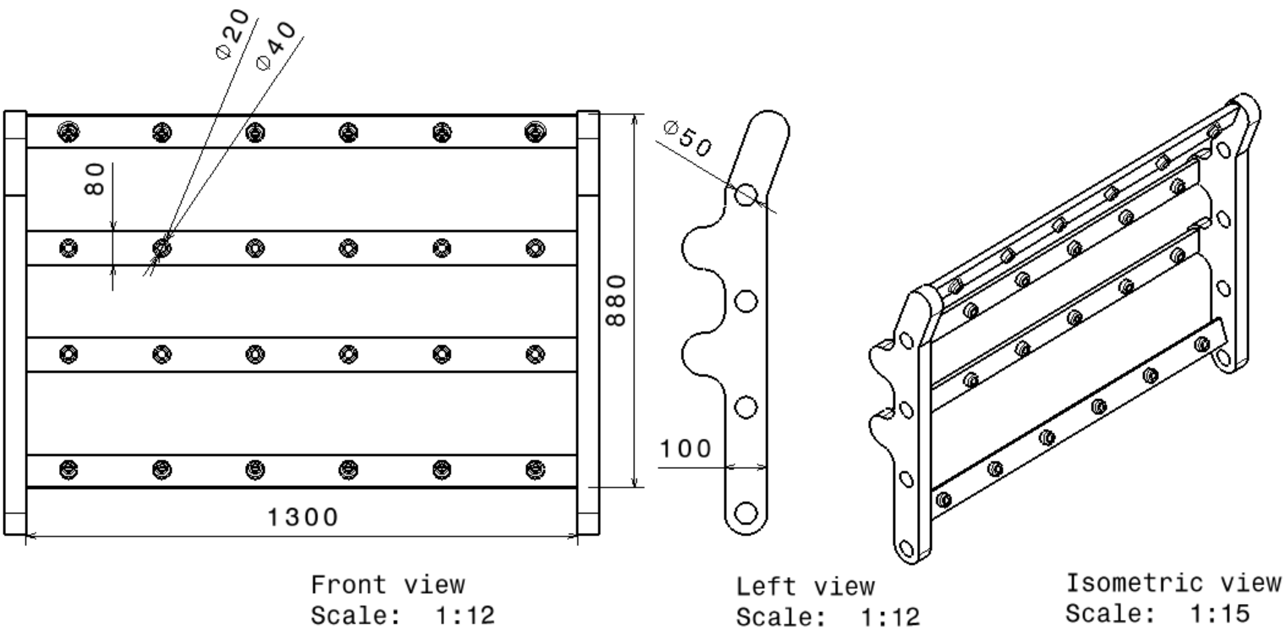
Figure 32. Accuracy and loss curves for AlexNet Using SGD Solver.

9.2. Technical specifications

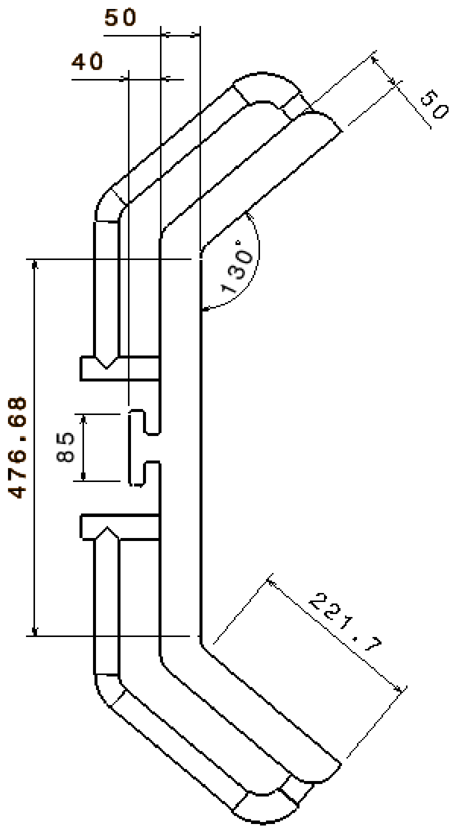
Race drawing



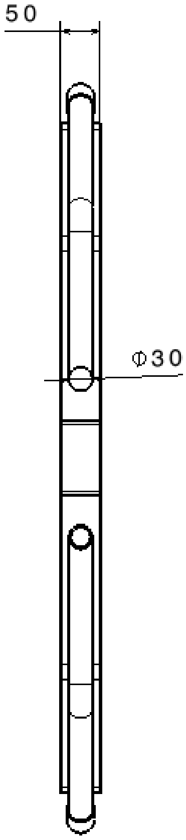
Nozzle Matrix Drawing



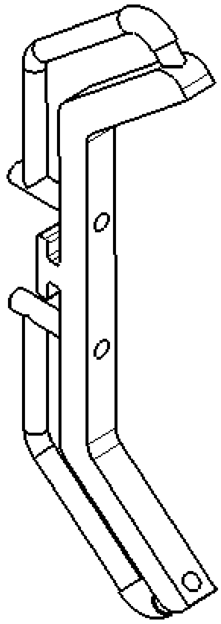
Nozzle Rack Drawing



Front view
Scale: 1:6



Left view
Scale: 1:6



Isometric view
Scale: 1:6

Servo motor data sheet

Servo Motor Specifications

Low Inertia Series

Model: ECMA Series	C△04	C△06		C△08		C△09		C△10		C△13
	01	02	04□S	04	07	07	10	10	20	30
Rated power (kW)	0.1	0.2	0.4	0.4	0.75	0.75	1.0	1.0	2.0	3.0
Rated torque (N-m)*1	0.32	0.64	1.27	1.27	2.39	2.39	3.18	3.18	6.37	9.55
Maximum torque (N-m)	0.96	1.92	3.82	3.82	7.16	7.14	8.78	9.54	19.11	28.65
Rated speed (r/min)	3000					3000		3000		3000
Maximum speed (r/min)	5000					3000		5000		4500
Rated current (A)	0.90	1.55	2.6	2.6	5.1	3.66	4.25	7.3	12.05	17.2
Maximum current (A)	2.70	4.65	7.8	7.8	15.3	11	12.37	21.9	36.15	47.5
Power rating (kW/s)	27.7	22.4	57.6	24.0	50.4	29.6	38.6	38.1	90.6	71.8
Rotor inertia (x10-4kg-m²)(without brake)	0.037	0.177	0.277	0.68	1.13	1.93	2.62	2.65	4.45	12.7
Mechanical constant (ms)	0.75	0.80	0.53	0.74	0.62	1.72	1.20	0.74	0.61	1.11
Torque constant-KT (N-m/A)	0.36	0.41	0.49	0.49	0.47	0.65	0.75	0.44	0.53	0.557
Voltage constant-KE(mV/(r/min)	13.6	16	17.4	18.5	17.2	24.2	27.5	16.8	19.2	20.98
Armature resistance (Ohm)	9.30	2.79	1.55	0.93	0.42	1.34	0.897	0.20	0.13	0.0976
Armature inductance (mH)	24.0	12.07	6.71	7.39	3.53	7.55	5.7	1.81	1.50	1.21
Electric constant (ms)	2.58	4.3	4.3	7.96	8.36	5.66	6.35	9.3	11.4	12.4
Insulation class	Class A (UL), Class B (CE)									
Insulation resistance	>100 MΩ, 500 V_{DC}									
Insulation strength	1.8k V_{AC}, 1 sec									
Weight (kg) (without brake)	0.5	1.2	1.6	2.1	3.0	2.9	3.8	4.3	6.2	7.8
Weight (kg) (with brake)	0.8	1.5	2.0	2.9	3.8	3.69	5.5	4.7	7.2	9.2
Max. radial shaft load (N)	78.4	196	196	245	245	245	245	490	490	490
Max. thrust shaft load (N)	39.2	68	68	98	98	98	98	98	98	98
Power rating (kW/s) (with brake)	25.6	21.3	53.8	22.1	48.4	29.3	37.9	30.4	82	65.1
Rotor inertia (x10-4kg-m²) (with brake)	0.04	0.192	0.30	0.73	1.18	1.95	2.67	3.33	4.95	14.0
Mechanical constant (ms) (with brake)	0.81	0.85	0.57	0.78	0.65	1.74	1.22	0.93	0.66	1.22
Brake holding torque [Nt-m (min)]*2	0.3	1.3	1.3	2.5	2.5	2.5	2.5	8	8	10.0
Brake power consumption (at 20°C) [W]	7.3	6.5	6.5	8.2	8.2	8.2	8.2	18.7	18.7	19.0
Brake release time [ms (Max)]	5	10	10	10	10	10	10	10	10	10
Brake pull-in time [ms (Max)]	25	70	70	70	70	70	70	70	70	70
Vibration grade (µm)	15									
Operating temperature (°C)	0°C to 40°C (32°F to 104°F)									
Storage temperature (°C)	-10°C to 80°C (-14°F to 176°F)									
Operating humidity	20 to 90% RH (non-condensing)									
Storage humidity	20 to 90% RH (non-condensing)									
Vibration capacity	2.5G									
IP Rating	IP65 (when waterproof connectors are used, or when an oil seal is used to be fitted to the rotating shaft (an oil seal model is used))									
Approvals	CE cULus									

Footnote:
*1 Rate torque values are continuous permissible values at 0~40°C ambient temperature when attaching with the sizes of heatsinks listed below:
ECMA-__04 / 06 / 08 : 250 mm × 250 mm × 6 mm
ECMA-__10 : 300 mm × 300 mm × 12 mm
ECMA-__13 : 400 mm × 400 mm × 20 mm
ECMA-__18 : 550 mm × 550 mm × 30 mm
ECMA-__22 : 650 mm × 650 mm × 30 mm
Material type : Aluminum F40, F60, F80, F100, F130, F180, F220
*2 The holding brake is used to hold the motor shaft, not for braking the rotation. Never use it for decelerating or stopping the machine.

Servo Driver data sheet

Specifications

ASDA-B2 Series			100 W 01	200 W 02	400 W 04	750 W 07	1 kW 10	1.5 kW 15	2 kW 20	3 kW 30
Power Supply	Phase / Voltage		Three-phase 170 ~ 255 V_{AC}, 50/60 Hz ±5% Single-phase 200 ~ 255 V_{AC}, 50/60 Hz ±5%						Three - phase 170 ~ 255 V_{AC}, 50/60 Hz ±5%	
Power Supply	Input Current (3PH) (Units: Arms)		0.7	1.11	1.86	3.66	4.68	5.9	8.76	9.83
Power Supply	Input Current (1PH) (Units: Arms)		0.9	1.92	3.22	6.78	8.88	10.3	-	-
Power Supply	Continuous Output Current (Units: Arms)		0.9	1.55	2.6	5.1	7.3	8.3	13.4	19.4
Cooling System			Natural Air Circulation				Fan Cooling			
Encoder Resolution			17-bit (160,000 p/rev)							
Main Circuit Control			SVPWM (Space Vector Pulse Width Modulation) Control							
Control Mode			Auto / Manual							
Regenerative Resistor			None		Built-in					
Position Control Mode	Max. Input Pulse Frequency		Transmitted by differential: 500K (low speed) / 4 Mpps (high-speed) Transmitted by open-collector: 200 Kpps							
Position Control Mode	Pulse Type		Pulse + Direction, A phase + B phase, CCW pulse + CW pulse							
Position Control Mode	Command Source		External pulse							
Position Control Mode	Smoothing Strategy		Low-pass filter							
Position Control Mode	E-gear Ratio		Electronic gear N/M multiple N: 1 ~ (2^{26} -1) / M: 1 ~ (2^{31} -1) (1/50 < N/M < 25600)							
Position Control Mode	Torque Limit Operation		Set by parameters							
Position Control Mode	Feed Forward Compensation		Set by parameters							
Speed Control Mode	Analog Input Command	Voltage Range	0 ~ ±10 V_{DC}							
Speed Control Mode	Analog Input Command	Input Resistance	10KΩ							
Speed Control Mode	Analog Input Command	Time Constant	2.2 μs							
Speed Control Mode	Speed Control Range*1		1:5000							
Speed Control Mode	Command Source		External analog signal / Internal parameters							
Speed Control Mode	Smoothing Strategy		Low-pass and S-curve filter							
Speed Control Mode	Torque Limit		Set by parameters or via analog input							
Speed Control Mode	Bandwidth		Maximum 550 Hz							
Speed Control Mode	Speed Accuracy*2		±0.01% at 0 to 100% load fluctuation ±0.01% at ±10% power fluctuation ±0.01% at 0 °C to 50 °C ambient temperature fluctuation							

Features/accesories of the Kinect hardware

Kinect hardware key features and benefits

Feature	Benefits
Improved body tracking	The enhanced fidelity of the depth camera, combined with improvements in the software, have led to a number of body tracking developments. The latest sensor tracks as many as six complete skeletons (compared to two with the original sensor), and 25 joints per person (compared to 20 with the original sensor). The tracked positions are more anatomically correct and stable and the range of tracking is broader.
Depth sensing 512 x 424 30 Hz FOV: 70 x 60 One mode: .5–4.5 meters	With higher depth fidelity and a significantly improved noise floor, the sensor gives you improved 3D visualization, improved ability to see smaller objects and all objects more clearly, and improves the stability of body tracking.
1080p color camera 30 Hz (15 Hz in low light)	The color camera captures full, beautiful 1080p video that can be displayed in the same resolution as the viewing screen, allowing for a broad range of powerful scenarios. In addition to improving video communications and video analytics applications, this provides a stable input on which to build high quality, interactive applications.
New active infrared (IR) capabilities 512 x 424 30 Hz	In addition to allowing the sensor to see in the dark, the new IR capabilities produce a lighting-independent view—and you can now use IR and color at the same time.
Kinect for Xbox One sensor dimensions (length x width x height)	9.8" x 2.6" x 2.63" (+/- 1/8") 24.9 cm x 6.6 cm x 6.7 cm Length: The Kinect cable is approximately 9.5 feet (2.9 m) long Weight: approximately 3.1 lbs (1.4 kg) Sensor FOV: 70 x 60
A multi-array microphone	Four microphones to capture sound, record audio, as well as find the location of the sound source and the direction of the audio wave.

Table taken from: https://developer.microsoft.com/en-us/windows/kinect/hardware

Easygrip Extra Large Camera Clamp

Easy Grip XL Specifications

- EasyGrip ST - grips flat or round surface from 0cm to 3.8cm
- EasyGrip LG - grips flat or round surface from 2.5cm to 6cm
- EasyGrip XL - grips flat or round surface from 0cm to 10cm
- Attaches to any round or flat object
- Fits any device with a 1/4 inch-20 tripod socket
- Durable, aluminum alloy clamp body and screw
- Positions device at any angle
- Maximum Safe Load: 2.72kgs
- Pan Adjustment: 360 degrees
- Tilt Adjustment: +/- 90 degrees
- Angular Adjustment: +/- 20 degrees

Taken from: http://www.kayellaustralia.com.au/easygrip-inches-wide-p-1438.html

9.3. Experimental results using four kinect cameras

Merged Point Clouds from Multiple Angles

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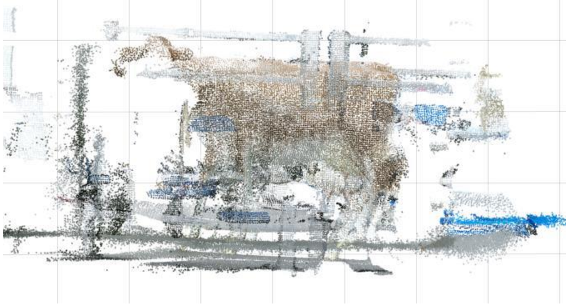
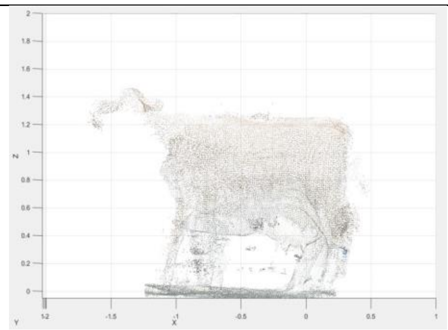
<tr><td></td><td></td></tr>
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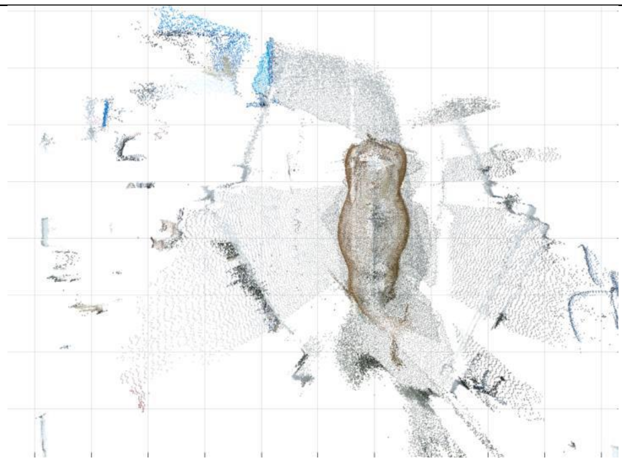
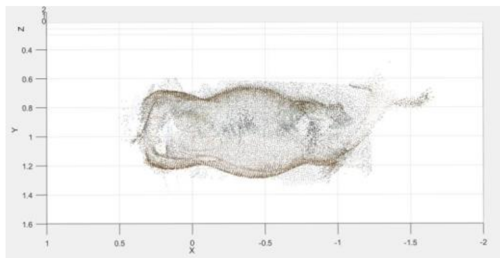
<tr><td></td><td></td></tr>
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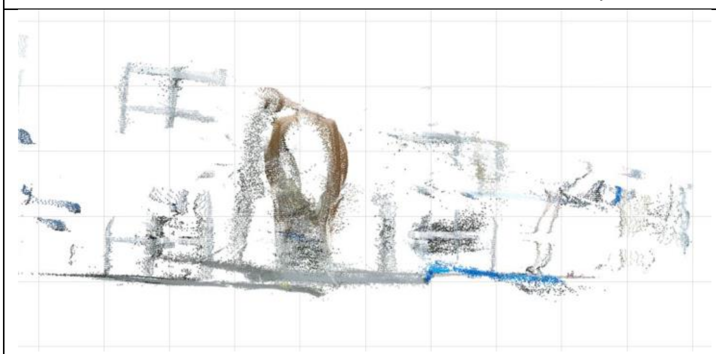
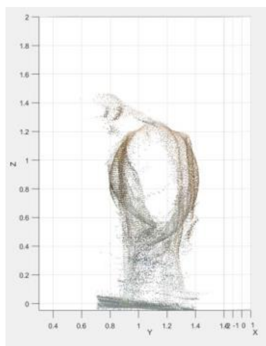
<tr><td></td><td></td></tr>
<tr><td colspan="2">Rear View</td></tr>
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