



# AUSTRALIAN POULTRY CRC

## FINAL REPORT

### Program 3A

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DATE OF COMPLETION: 31 August 2007

Project No: CRC 06-11

**Using machine vision to count hens  
and reduce egg breakage – proof of  
concept.**





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ISBN 1 921010 05 3

*Using machine vision to count hens and reduce egg breakage – proof of concept.*  
*Project No. CRC 06-11*

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Published in November 2007

## Executive Summary

‘Machine vision’ or automatic video image analysis (VIA) is the ability of a computer to ‘see’. This technology provides the opportunity to replace humans in the performance of certain mundane, repetitive or difficult tasks that require decision-making, and to perform the tasks at greater speed and with lower error rates. VIA involves the use of one or more cameras and the application of software that can process digital (video) images. Within those images the software (algorithms) detects and tracks target(s). The software also incorporates further logical functions, for example, reporting the presence of the target, counting the number of targets, or based on a decision-making function, sorting different targets.

VIA is used in many industrial situations to monitor production processes and provides a mechanism for automatic decision-making. In the agricultural industries, VIA is used for example, as a tool to facilitate rapid, accurate and automatic grading and sorting of fruit and vegetables and to examine and sort meat chicken carcasses. Quality assurance can also be performed at low error rates due to the removal of human error and this is used extensively in horticulture. While the use of VIA as a tool in animal research is increasing, the practical application of VIA technology in animal production is much less common. The opportunity exists to apply VIA in intensive animal production industries, such as the modern cage egg industry, to improve productivity and the efficiency of labour use. Increased frequency of surveillance of the animals and the mechanical processes occurring within the animals’ environment is possible, with improved attention to detail.

More frequent monitoring of animals and mechanical equipment may also assist pro-active rather than reactive management through the earlier identification of risk situations that may impact on the animal’s health or welfare or on the production process. Another benefit is that automatic monitoring is possible under adverse situations, such as in low light conditions including total darkness (through the use of infra-red illumination) or in less accessible locations such as at heights in upper tiers of modern, multi-tier cage egg housing. Further, by automating the surveillance of animals or processes (eg. the mechanical egg collection belt) and the reporting of problems to the stockperson, more time would be made available to the stockperson for less-mundane tasks.

This proof of concept project investigated the potential to use VIA to count hens in cages and to monitor the egg collection belt to detect obstructions. Counting hens in cages was considered as a first step in being able to monitor hens automatically leading to a mechanism for automatic monitoring of bird welfare and health. Monitoring the egg collection (conveyor) belt to detect potential blockages would provide an automatic alert system to detect risk situations that may result in increased incidence of cracked and broken eggs. In the project, robotic feeding machines were used to transport miniature cameras along the rows of cages to permit the application of VIA.

Two prototype machine vision systems were developed to count hens in cages utilising two targets on the birds (eyes and legs). Only the leg-target showed potential for counting hens in cages. The ‘leg-scan’ software detected 79% of visible legs in our evaluation trials. However, better positioning of the camera would greatly improve the detection rate.

The project also successfully developed a prototype to detect potential blockages on the egg collection belt. The ‘egg-belt scan’ software detected 95% of foreign objects, that is non-egg objects. Further refinement of the software will improve the detection rate.

In addition, the opportunity exists to refine the 'leg-scan' software further to detect dead hens inside cages. Dead hens appeared to be one of the main causes of egg belt blockage at the commercial farm, and thus by addition this component of the software, the accuracy of the egg-belt scan software should be further improved.

The project proves the concept that VIA can be applied to count hens and monitor egg belts. The two variations of VIA software developed, 'leg-scan' and 'egg-belt scan', have genuine practical application to the modern cage egg industry. The knowledge gained in this project will also assist the use of the technology in other livestock situations. Probably the biggest factor limiting the further application of the technology is one's own imagination.

- It is recommended that the Australian Poultry CRC discusses these results with relevant cage manufacturers / suppliers, with the view to commercialisation.
- Further research is required to:
  1. refine the leg-scan and egg-belt scan prototypes and software, and
  2. refine a finding of the project to recognise dead hens in cages.

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# 1 Introduction

Labour is a major cost component affecting farm profitability. One strategy to reduce labour costs per unit of production has been to intensify production methods, enabling increased number of animals per farm and per labour unit. In the modern cage egg industry, birds are housed in multi-tier systems inside climate-controlled sheds and mechanical (and to some degree automatic) procedures provide feed to the birds, collect the eggs and remove the manure, contributing to labour savings. However, whether the use of large multi-tier systems necessarily leads to the expected degree of labour savings is not known. Rather than a linear reduction in the amount of labour required per bird, modern cage housing systems possibly require more labour than expected due to the need to perform 'new' tasks. One such 'new' task for the stockperson in modern cage systems with mechanical (conveyor belt) egg collection, is to monitor the egg collection belts for obstructions before the egg collection process commences each day. An obstruction, such as a dead bird or other foreign object on a collection belt, may impede or totally block the movement of eggs as the belt moves along the front of the cage row. At a total blockage eggs cannot pass the obstruction, will bank up and possibly spill over the side of the egg tray. In production terms the outcomes are a loss of eggs from down-grading (cracked) or breakage (total loss) and a time cost incurred for any clean-up required. Another daily task for the stockperson is to conduct a 'thorough welfare inspection' of the birds in every cage. This is a requirement under the Model Code of Practice for the Welfare of Domestic Poultry (Primary Industries Standing Committee, 2001). In sheds with multi-tier housing above head height, stockpeople require some form of equipment (eg. a mobile platform) to assist the inspection of birds in the upper tiers. According to the Big Dutchman sales brochure (January 2005), the heights of their 4- and 8-tier cage systems are 2.55 m and 5.11 m, respectively. Thus, monitoring of the upper tier levels in cage systems with 4- or more-tiers, may require additional stockperson time for inspection of birds and checking the egg collection belt for blockages.

Failure to adequately monitor upper tier cages for dead birds can contribute to inefficiency of production if the dead birds gravitate onto the egg belt and contribute to egg belt blockage. Thus the detection and removal of dead birds in upper level cages and other foreign objects on the upper level egg collection belts are important tasks that may require additional stockperson time compared to surveillance of the lower tiers. The incidence of egg belt blockages in the upper tier levels, eg. those above head height of the stockperson compared to the lower (more visible) tiers, and labour down-time associated with the respective blockages, does not appear to have been studied but could contribute to a significant waste of stockperson time and lower farm economy. The present project tested the proof of concept of applying "machine vision" to some routine surveillance procedures associated with egg production from modern cage systems involving multi-tier housing with automatic egg collection. If proven, the technology could provide a means to improve the efficiency of labour use while improving the frequency of surveillance, potentially leading to reduced egg wastage and better bird welfare.

Machine vision, or automatic video image analysis (VIA), is defined as the ability of a computer to 'see'. In a machine-vision system, one or more cameras supply information to a high speed computer, and depending on the software written for the specific application, stationary or moving objects can be recognised and tracked. Machine vision has been applied in industrial situations for more than 10



years to automate decision-making and to record linear measurements of objects or other data such as serial numbers, on moving production lines. A recent example of VIA in commercial chicken meat processing reported rapid (140 birds per minute) and automatic inspection of moving chicken carcasses on the production line. A machine vision system using colour cameras was developed and implemented to detect and record carcass size and shape, while simultaneously identifying imperfections such as local tears, bruises and tumours, and bacterial infections on the carcass not visible to the human eye. Carcasses were then automatically sorted according to the information provided by the machine vision.

This one-year proof of concept project aimed to determine whether VIA technology could be applied to the modern cage egg industry. The project tested the concept that VIA could be used to:

- 1) count the number of live hens per cage (with multiple hens per cage), within a row of cages, and
- 2) identify potential blockages of the egg conveyor belt that may result in damaged eggs.

## 2 Review of automatic video image analysis

Machine vision or automatic video image analysis (VIA) is a technology that provides the opportunity to replace humans in the performance of certain mundane, repetitive or difficult tasks that require decision-making, and to perform the tasks at greater speed and with lower error rates. The VIA process involves video monitoring the performance of a procedure by cameras linked to a computer. Software registers the procedure and makes logical decisions to provide faster and more accurate task performance.

There are many current developments and applications of VIA in agriculture and other industries. Two recent publications from international conferences provide examples of how VIA is being applied for many different and varied purposes (*viz.* Precision Agriculture '05 – 5<sup>th</sup> Biennial Conference on Precision in Agriculture, Uppsala Sweden, J.V. Stafford (ed.) 1005 pp. and Measuring Behavior 2005 – 5<sup>th</sup> International Conference on Methods and Techniques in Behavioral Research, Wageningen The Netherlands, M.R. Ballintijn *et al.* (eds.)).

Using VIA to automatically track or monitor moving objects, such as experimental animals in research projects, is common (eg. Ethovision® by Noldus BV). However, application of this technology to monitor the health, welfare or production of commercial livestock on farms is a relatively new concept that is yet to be widely applied.

The VIA process requires either the streaming of a digital video signal to a high speed computer with appropriate software to recognise a 'target' amongst the pixilated data, or capture of the video stream onto a storage medium for later analysis. Digital images are in fact electrical information represented by shades of grey or colour hues on a TV monitor to the human observer. VIA software however can interpret changes in the electrical content of successive digital images, and thus pixels, as movement of the target. Depending on the software application, the computer may either follow (ie. 'track') a target attached to an object or the whole object, or analyse the image in some way and make a decision about what to do with the object.

A major area of interest for the application of VIA is in production grading. VIA has been applied in industrial situations for more than a decade to automate decision-making and to record linear measurements of objects on moving production lines. Machine vision has been successfully applied in

many fruit and vegetable sorting procedures (see review by Zheng *et al.* 2006). Applications have also been reported in the poultry industry. For example, Comis (2002a) reported rapid (140 birds per minute) and automatic inspection of moving chicken carcasses on a production line. Robotic cameras (ie. ‘machine vision’) detected and recorded carcass size and shape, while simultaneously identifying imperfections such as local tears, bruises and tumours, and bacterial infections on the carcass not visible to the human eye. Carcasses were then automatically sorted according to the information provided by the machine vision. For the egg industry, Mertens *et al.* (2005) described a system of using VIA to detect defects and dirt on brown eggs, with excellent results (0% false negatives, 2% false positives, n=200). Mertens’ system, however, required complex lighting and egg manipulation infrastructure, which was generally expensive and difficult to retrofit to existing production facilities.

There are many other reported industrial applications in which a moving object or product is assessed using VIA. Examples include:

- automatic sorting of pieces of fruit, mineral ore, etc. based on object colour, size and/or imperfection of the surface [see Adept Vision Systems website – [www.adept.net.au](http://www.adept.net.au)].
- quality assurance assessment of apple juice based on bacterial contamination (Comis, 2002b).
- monitoring of shoppers in supermarkets to alert management to the impending requirement for additional cash register operators (de Vries, 1997).
- monitoring of crowds to detect dangerous behaviour (Cupillard *et al.*, 2005; Foresti *et al.*, 2005).
- applications of image features (colour, size, shape and texture) for food quality evaluation and inspection (Zeng *et al.*, 2006).

A number of experimental uses for VIA have been applied in animal production. Mostly applications have been designed to reduce handling of the animal in comparison to traditional methods and are aimed at the survey of linear or angular measures on cattle and pigs (Barbera, 2003; Brandl, 1997; Chedad *et al.*, 2000; Schofield *et al.*, 2002). In the chicken meat industry, Sergeant *et al.* (1998) used VIA software to detect and track broiler chickens in a group situation to identify the birds interacting with the drinker and feeder, whereas Bizeray *et al.* (2002) used VIA to monitor activity in broiler chickens as a potential tool to predict onset of leg problems as the birds grew. In the United States egg industry, Patel *et al.* (1998) described a system using neural networks to perform inspection of eggs for defects (grading) using VIA. Neural networks are a set of software procedures that simulate learning with weighted links between ‘nodes’ of the system (or network). The software was first trained, by presenting multiple images with known results, to detect blood spots, dirt stains and cracks. The neural network, presented with an unknown image, then provided an output based on the generalisation of what it had ‘learned’ from the training images. While the authors reported a moderate degree of success (80% to 92.8%) sufficient to produce graded samples that exceeded the USDA requirements, performance of the system was decreased if eggs had more than one defect.

Motion tracking and VIA have been applied to a number of different research and clinical situations as a tool to analyse complex biomechanical movements of humans and animals, eg. to study gait, muscle movement, force generation, etc. (Delp and Loan, 2000), or the interaction between humans and machines (usability testing). An extension of the former has been the development of sports simulation models to improve the athletic performance of humans and animals. The objective measurement of complex biomechanical movements such as gait, should increase the accuracy of measurement by eliminating human error and thus facilitate the conduct of experiments, by automating data capture and collation. The latter is especially true of experiments in psychology and pharmacology, involving laboratory animals as test subjects. Indeed, there are many potential uses for automatic VIA which

provide advantages of greater flexibility and accuracy over manual recording systems, provided the tracked object can be distinguished (based on contrast) from the background.

The research reported here was conducted in consultation with Mark Dunn, who recently completed his PhD with the National Centre for Engineering in Agriculture, University of Southern Queensland. Mark's PhD was titled "Machine Vision in Agriculture". As part of his PhD work, Mark developed video image recognition and capture software for application to livestock industry uses. Mark is recognised as co-author on this Final Report.

In the poultry industry there are many potential opportunities where 'machine vision' could be applied to improve the efficiency of labour use, potentially leading to reduced labour costs, and improved animal production and welfare. The present project tested the concept of machine vision for the modern cage layer industry to monitor the birds and the egg collection belt. Automation of these tasks could improve the efficiency of labour use, potentially reducing the proportion of work time stockpeople spend conducting monotonous tasks, while increasing the frequency of surveillance of birds and egg collection belts to detect risk situations and to issue an alert.

### **3 Objectives**

The objectives of the project were to test the proof of concept that automatic video image analysis (ie. machine vision) could be used to 1) count live laying hens in cages and 2) identify egg belt blockage. The project tested the hypotheses that machine vision can be applied to 1) count the number of live birds per cage and 2) identify when a foreign object (that may obstruct the egg belt) was present.

The work has two broad (long-term) aims: First, to improve hen welfare in cages through increased frequency of surveillance while minimising human labour inputs. Second, to reduce egg wastage from egg collection belts while minimising human labour inputs. The strategy for the research involved applying 'machine vision' technology to intensive animal production to improve economic and social outcomes for egg producers and poultry stockpeople, and hen welfare.

### **4 Methodology**

Prior to testing the VIA software on a commercial farm, it was necessary to simulate the process in a more-controlled situation. In the first component of the project a robot was purchased and commissioned at DPI Werribee. The robot enabled the development and refinement of a VIA system for use in a cage layer shed before commencing the second component of the project which was conducted at a commercial farm that used robotic feeding machines. The robot provided the mechanism to transport cameras within the poultry shed and thus enabled the concept of VIA to be evaluated in a modern cage egg production system.

The DPI Werribee research was conducted in a controlled environment, poultry research shed containing a bank of Victorsson Trivselburen 8-bird cages (AB Bröderna Victorsson, Sweden). The bank of 'back-to-back' cages was 5 cages long and 3 tiers high and the individual cages within the bank measured 1.2 m wide, 0.5 m deep and 0.53 m high at the front. In order to better understand hen responses to the presence of a 'robot', the behaviour of the hens was observed before and after the

installation of the robot. The observations also provided information to identify potential targets that may enable the counting of hens in cages using VIA technology.

The on-farm component of the project was conducted in a controlled climate shed containing Salmet 8-bird layer cages. There were 4 banks of 'back-to-back' cages in the shed and the banks were 6 tiers high. The individual cages measured 0.7 m wide, 0.57 m deep and 0.45 m high at the front. Each bank of cages was serviced by a robotic feeding machine which moved at 8.6 m/min when providing feed to the feed trough. Egg collection and manure removal were mechanised using conveyor belts.

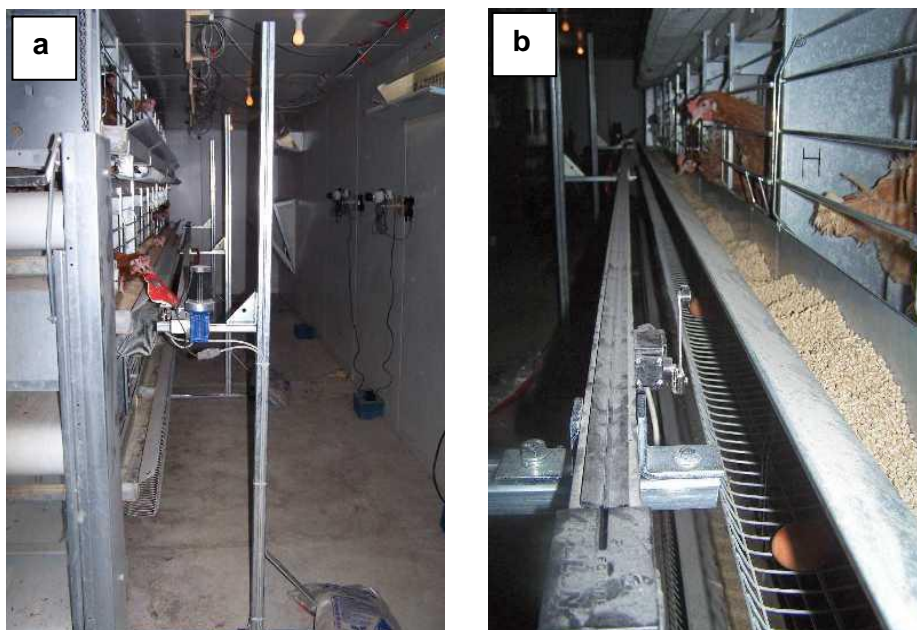
Black and white and colour miniature CCD cameras (QC3494 and QC3468, respectively, Jaycar) with PAL-B analogue output were attached to the robots to record video sequences for the project. The signals were converted to a digital video stream using a Belkin F5U208 USB adapter and were recorded as digital files on computer hard drives.

#### 4.1 Set-up of robot at DPI Werribee

The Werribee 'robot' was bolted onto a motor-mounting plate top, which could move along a 6-m Ecoline XM37 linear guided track. The track system contained a transmission belt driven by a Pacific Scientific High Torque stepper motor (model T23NRLC-LNN-NS-00, Figures 1, 2a and 2b). Speed and direction of movement of the motor, and the time between commencing movement after reaching either end of the track (ie. in the opposite direction) could be controlled.

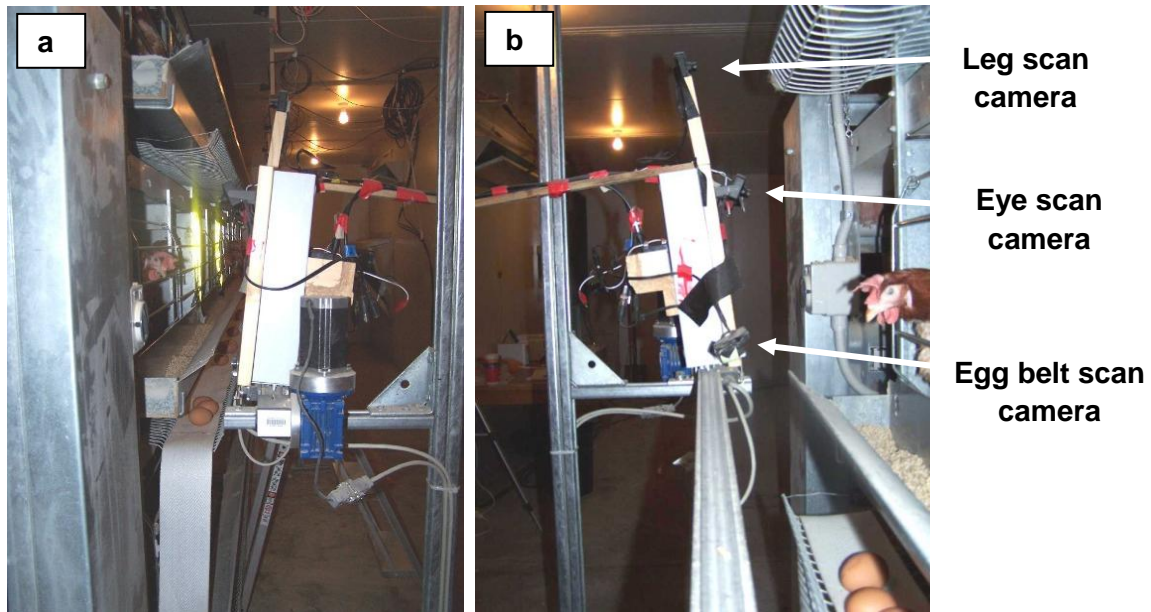


**Figure 1. The drive motor for the robot installed at DPI Werribee.**

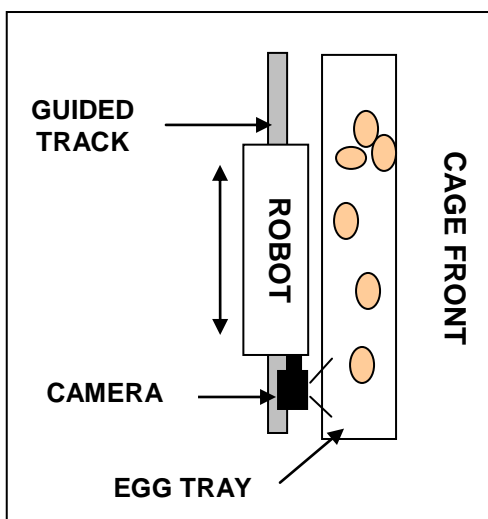


**Figures 2a and b. Position of the robot motor and guided linear track in front of the cages at DPI Werribee. The left view shows the lay-out from the drive motor end of the track. The right view shows the track from the opposite end.**

A metal box measuring 30 x 30 x 10 cm was used to simulate a robotic feeding machine (Figures 3a-c). The metal box could move along the guided track which was supported about 1.1 m above floor level and 25 cm from the front of the cages. The distance from shed floor to cage floor in the middle tier of cages, where the eye scan and egg belt scan observations were conducted, was 0.95 m. The leg scan observations were conducted using the top tier of cages.



**Figures 3a and b. Position of the robot box and track in front of the cages at DPI Werribee. The left view shows the lay-out from the drive motor end of the track. The right view shows the track from the opposite direction and the 3 cameras. Conveyor belt material was positioned over the egg collection tray to simulate the egg collection belt used at the commercial farm.**



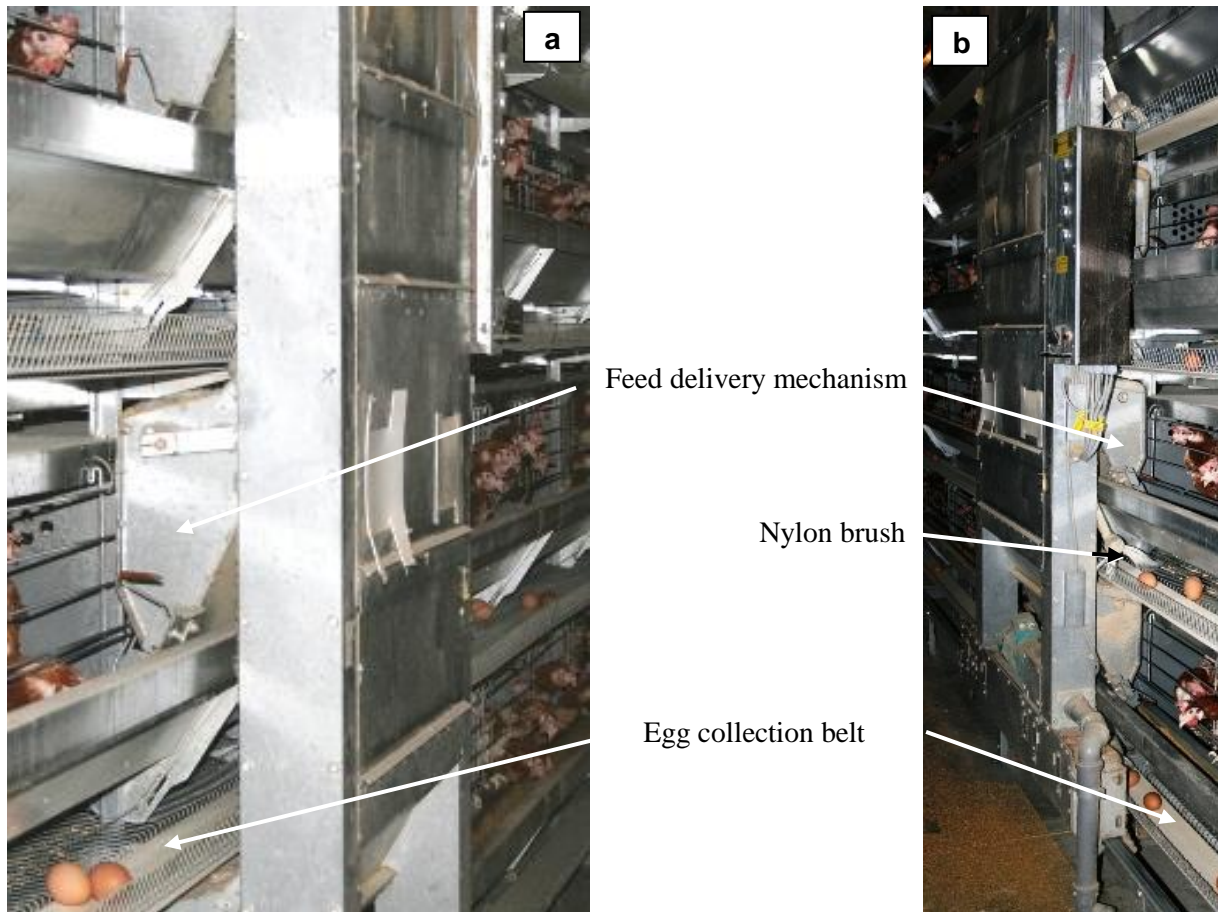
Three miniature CCD cameras were attached via a wooden frame to the ‘robot’, to provide video images of the egg collection belt, and views inside cages to facilitate scanning for hens’ eyes and legs (Figure 3b). For infra-red (IR) video recording, the IR light was provided by light emitting devices (LED) incorporated onto the front of the camera, adjacent to the lens. For colour video recording the field of view was illuminated by a “Mighty Bright Book Light” (Collins Book Sellers) with a blue gel filter (Rosco #3202 ‘Full Blue’, Rosco Gels).

**Figure 3c. Schematic representation from overhead showing the position of the robot and egg belt scan camera, relative to the egg tray, which was positioned below the feed trough.**



## 4.2 Set-up of robot at Kinross Farm

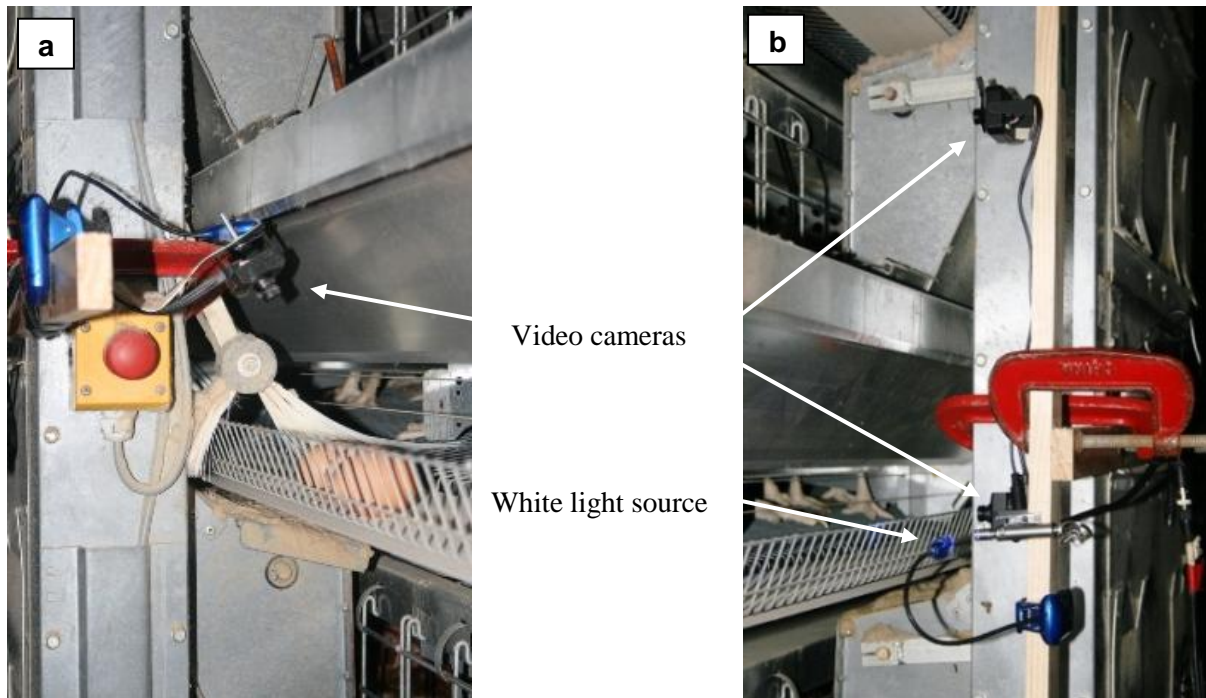
The robotic feeding system at Kinross Farm was used as the means to transport miniature CCD cameras along the line of cages for the second component of the project. The cage system at the farm was 6 tiers high and our measurements were conducted using the third tier of cages from the bottom. The robotic feeder is shown in Figures 4a and b prior to attachment of the cameras.



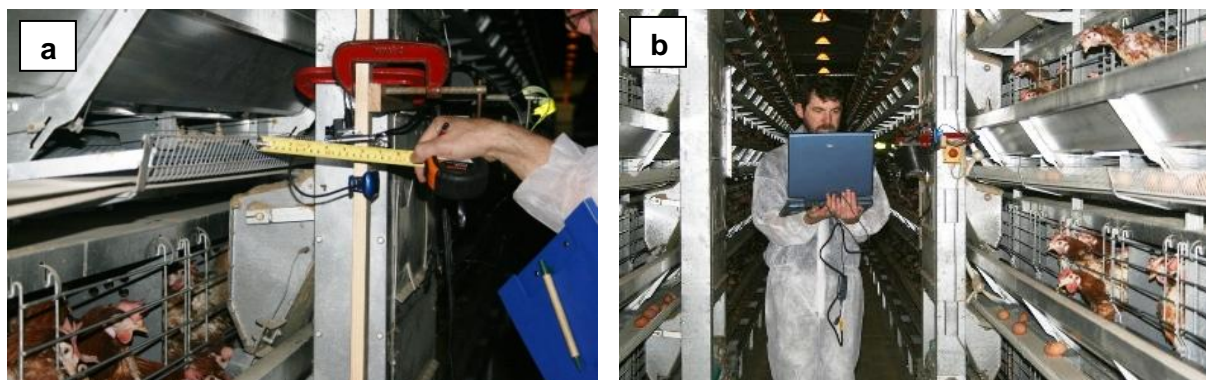
**Figures 4a and b. Pictures of the robotic feeding machine at the commercial farm, from the left (a) and right (b) hand perspectives. The robot delivered feed to the trough in front of each cage. A nylon brush is visible in the right picture. The function of the brush was to assist movement of eggs onto the egg collection belt.**

G-clamps were used to attach a wooden frame to the rear of the robotic feeding machine (Figures 5a and b). The three miniature CCD cameras were attached to the wooden frame to provide (1) a view of the egg collection belt from above and (2) two views into the cages. The latter two cameras were positioned as shown in Figure 5b to provide views of the hens' heads/eyes and legs, respectively. A clip-on white light source ('Mighty Bright Book Light') with blue filter (Rosco #3202 'Full Blue', Rosco Gels) and a clip-on blue LED ('Serpent light', Bunnings) were also attached to the wooden frame. These light sources provided illumination to the egg collection belt and leg-count scan fields, respectively, to assist the colour video recording, whereas IR lighting for the eye-count scan was provided by built-in IR LEDs on the front of the respective camera. The cameras and light sources

were positioned at predetermined distances and angles from the egg collection belt and cage front (Figure 6a). These measurements and angles were determined in previous trials conducted during refinement of the software at DPI Werribee. Once the cameras were correctly positioned, the machine vision system was calibrated (Figure 6b).



Figures 5a and b. G-clamps were used to attach a wooden frame to the feeding robot. The cameras and lights were then attached to the wooden frame. The camera shown in Figure 5a was positioned to scan the egg collection belt. In Figure 5b the upper camera was used to scan for eyes while the lower camera was used to scan for legs.



Figures 6a and b. The miniature CCD cameras were positioned according to predetermined distance and angle measurements, before the system was calibrated using a lap top computer. The photo on the right shows Mark Dunn calibrating the software.

## 5 Software development and results

The software used in this project was developed by Mr Mark Dunn (National Centre for Engineering in Agriculture, University of Southern Queensland). The software architecture was based on machine vision software previously developed by Mark as part of his PhD research.

The machine vision algorithms were created specifically for this project. The software was written using Microsoft Visual Studio C++ using DirectShow technology, part of the Microsoft DirectX suite. These tools provide a hardware invariant platform for video and audio manipulation.

So that images derived from an array of video data can be processed, a defined feature or target is required that can be detected by the software. Target(s) for identification by machine vision software are stored as a catalogue of items, and during software development, data reduction progressively occurs, refining and improving the ability of the software to ‘understand’ images or a sequence of images.

The required outputs for the present project were to identify appropriate target(s) that could be ‘recognised’ by the software. The project investigated the ability of machine vision technology to monitor two aspects of cage egg production and related to whether machine vision could:

1. Count hens in cages, and
2. Scan the egg collection belt and differentiate between eggs and foreign objects.

To evaluate whether recognition of the targets by the developed software were acceptable/reliable in a practical situation, the adapted software and hardware were initially developed and refined under controlled experimental conditions at DPI Werribee before testing the ‘system’ on a commercial farm.

### 5.1 Counting hens by eye

Our approach to counting the number of hens per cage required consideration of the conditions in which commercial hens are housed. Hens in modern cage egg production systems are housed in environmentally controlled sheds, usually in groups of 5 to 8 birds, although larger cages which hold more birds are available commercially. While the spatial conditions might seem ideal for video recording, light is maintained at a relatively low level. The use of VIA to detect individual birds under conditions of low light intensity is virtually impossible in the visible spectrum with current technology. Current industrial machine vision systems require relatively high light levels as a prerequisite. Low light conditions, such as those occurring in poultry sheds, thus challenge machine vision systems. For example, the contrast between the target (bird or component of the bird) and the background is diminished due to low light. This problem is exacerbated because all birds in the cage are likely to have the same feather colour, meaning that the background could be the same colour and texture as the target. Another problem is that all hens may not be present simultaneously at the feed trough (ie. at the front of the cage), so some birds would be at a greater distance from the camera than others, and thus in even lower light intensity than birds at the front of the cage.

Our initial approach to counting hens was by detecting and tracking eyes, which involved the application of IR light. We have previously demonstrated (Cronin and Desnoyers, 2005) that the behaviour of hens in furnished cages, including inside the nest box, can be video recorded in low-light conditions and in total darkness using miniature low-light CCD black and white cameras, with



illumination provided from IR light sources. The IR light is emitted by in-built LED on the front of the camera adjacent to the lens. Our black and white video records showed that the retina of the hen absorbed IR light so that the hen's eye was represented in the video image as a black spot. Fortunately the skin (including the feathers) surrounding the hen's eye is relatively reflective of IR light, providing a contrasting background to the black spot of the eye. Each hen therefore, has a similarly-shaped 'target' on each side of its head when viewed under IR light, that contrasts with the immediate background area, formed by the combination of non-reflected (absorbed) and reflected IR light, respectively.

Our proposal for counting the number of hen eyes in a cage involved directing IR light into the cage. Assuming the hens looked at the IR light source, any IR light entering the eye would be absorbed with nil or minimal reflectance back to the camera. On the video image the hen eye should thus be detected as a black spot, whereas the IR light should reflect off the skin around the eye and be detected by the low-light, black and white camera as a bright area (ie. surrounding the black shape formed by the eye). The target recognition software could thus 'count' the number of eyes detected as a measure of the number of live hens in the cage. Sample colour and IR-lit video scenes of hens (Figures 7a and b) show hens' eyes under the different lighting situations to enable a comparison of the respective recorded images.



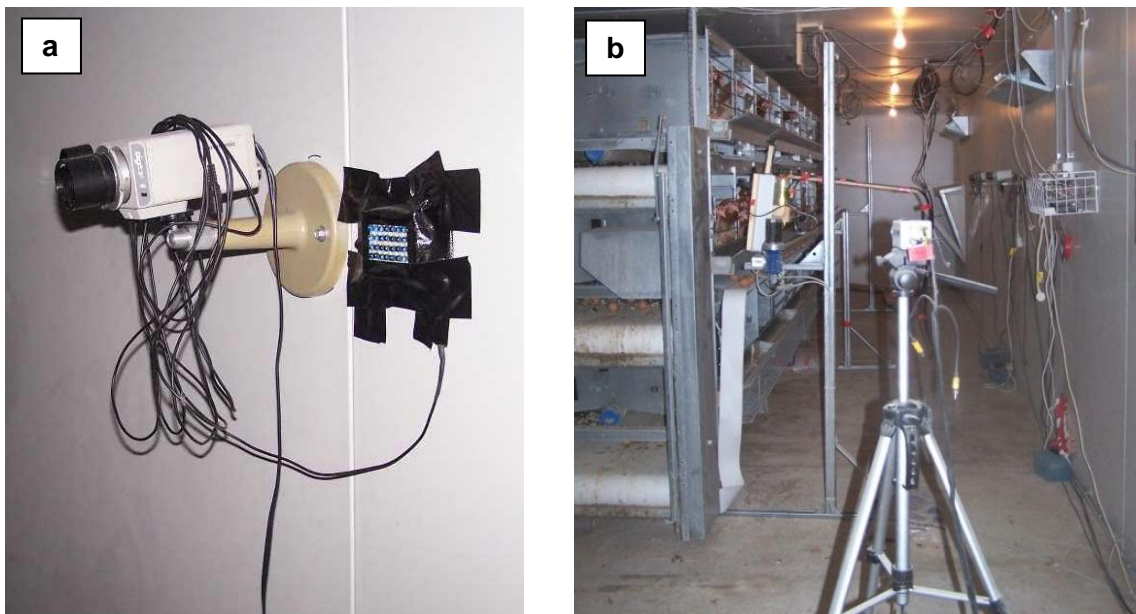
**Figures 7a and b. Colour and infra-red images of hens in cages illustrating the eye of hens as a potential target for image recognition and tracking using video image analysis to count hens.**

### **5.1.1 Behavioural response of hens to a passing robot**

To better understand how hens behaved in response to a passing robot with attached miniature CCD cameras and lights, and how the hens' behaviour near the moving robot affected the visibility of 'eye' targets, hens in two cages were recorded using fixed video cameras. For the observations a total of 30 Hy-line Brown laying hens were housed in five adjacent cages in Poultry Welfare Shed 2 at DPI Werribee. Each cage was 1.2 m wide and the five cages were one side of a bank of 10 cages, in the middle tier of a 3-tier bank of cages. The number of hens per cage ranged from 4 to 8 hens. The hens were maintained on a 16 h light to 8 h dark cycle and during the light phase the shed lighting provided 6 lux measured at 1 m above floor level.

Two video cameras (Panasonic WV-BP334 Black and White) with 6.0 mm lenses were mounted on the shed wall directly opposite the row of cages (Figure 8a) about 1.2 m above shed floor level. Each camera provided a view of one cage (cages 2 and 4, respectively), which was assisted by bank of IR LED positioned adjacent to each camera to enable video recording in the low-light conditions within the cages. The distance from the front of the cameras to the cages was approximately 1.4 m. A third camera was positioned on a tripod at one end of the row of cages to provide a view of the fronts of all five cages and the guided linear track along which the robot could move, and thus the robot as it passed the cages (Figure 8b).

The three cameras were connected via RG59 cables to a stand-alone computer located in a small room within Poultry Welfare Shed 2, but outside the experimental room. The computer recorded the streaming video data and the digital files were recorded in a native video format called VG (VG Player Version 5.3, Chateau Technical Group).



**Figures 8a and b. Photograph on the left showing one of the two wall-mounted video cameras with infra-red LED light bank, opposite the front of observation cages. Photograph on the right shows a view of the testing site from behind the video camera on the tripod.**

#### ***5.1.1.1. Video observation of hens in the cages before installation of the robot***

The hens in the two selected cages (cages 2 and 4) were continuously video recorded over three consecutive days using the cameras positioned opposite the cages. Cage 2 contained 5 birds and cage 4 contained 8 birds. The recording was conducted after the guided track system had been constructed, but prior to attachment of the robot (box) to the track system. At the completion of the 3 days of video recording, data were collated from the video records using a scan-sampling technique. The records were examined at six time points, 10 s apart, during the first minute of each hour from 10.00 h to 15.00 h. Thus 30 observations were recorded per cage per day. An observer recorded (1) the number

of hen eyes visible on the video image and (2) the behaviour of each hen. Hen behaviours recognised were:

- stand immobile
- locomote (walk)
- feed at trough
- drink (peck drinker)
- preen while standing
- sit
- hen was not visible

The purpose of the observations was to provide base line data in the absence of the robot, on visibility of the hens' eyes (considered a potential target for tracking) and hen activities. The behaviour scans showed that on average over the 3 observation days, 25% and 33% of hens' eyes, respectively, were visible in the cages with 5 and 8 birds (Table 1). The observations also suggested that increasing the number of hens per cage increased the frequency of occasions in which hens were not visible on the video image. It was thus concluded that the hen eye may not be an appropriate target for a machine vision system.

**Table 1. The proportion of hen eyes that were visible in the video images and the proportion of observations collated from recorded video images in which the hens performed the different behaviours. The values shown are percentages averaged over 3 observation days.**

<b>Parameter</b>	<b>Cage 2 (5 birds)</b>	<b>Cage 4 (8 birds)</b>
Proportion of hen eyes visible on video images	25%	33%
<b>Hen behaviour:</b>		
Stand immobile	60.2	42.5
Locomote	2.2	0
Feed at trough	15.6	28.1
Drink	2.2	0.5
Preen	11.5	13.2
Sit (squat)	4.4	5.9
Hen not visible	3.9	9.8
Total	100.0%	100.0%

#### **5.1.1.2 Video observation of hens in the cages after commissioning of the robot**

Hens were video recorded during days 2 and 3 following commissioning of the robot at DPI Werribee. On day 1 the robot travelled in front of the cages from 12.30 h to 16.30 h. The robot travelled at 0.9 m per min and there was a 60 s period of inactivity at the end of each trip along the track before the robot returned in the opposite direction. Due to one bird becoming ill in the 5-bird cage, the hen had been removed leaving cages with 4 and 8 birds, respectively. To improve our ability to observe the hens, only data from the 4-bird cage were collated. The observation technique used was similar to that

described above in Section 5.1.1.1. However, in each observation period the hens were observed during the 60 s:

1. before arrival of the robot in the field of view, and
2. after the robot had departed from the field of view.

As shown in Table 2, the proportion of hens' eyes that were recorded in the pre- and post-robot traverse were 23.6% and 21.9%, respectively. Table 2 also shows the occurrence of different behaviours performed by the hens prior to and following the robot passing the cage front.

**Table 2. The proportion of hen eyes visible and the proportion of observations that the 4 birds in the observation cage were recorded performing the different behaviours. The values shown are percentages averaged over 2 observation days.**

<b>Parameter</b>	<b>60 s pre-robot traversing</b>	<b>60 s post-robot traversing</b>
Proportion of hen eyes visible on video image	23.6%	21.9%
<b>Hen behaviour:</b>		
Stand immobile	75.0	74.3
Locomote	0	4.5
Feed at trough	14.9	9.0
Drink	2.4	5.9
Preen	7.3	5.6
Sit (squat)	0	0.3
Hen not visible	0.3	0.3
<b>Total</b>	<b>100.0%</b>	<b>100.0%</b>

Based on the low incidence of hen eyes in the video images, it was apparent that attempts to track hens' eyes using VIA would be quite difficult. It was noted that hens often moved their head rapidly, further contributing to the difficulty of using eyes as a target to count hens. Other potential targets were also considered with the hens' legs suggested as another option for testing.

## **5.1.2 Algorithms for eye tracking**

The main thrust of this application is the detection of specific 'targets' – in this instance the hens' eyes, in a semi-constrained image. There are a number of known constraints that can simplify the image analysis processing.

### **5.1.2.1 Camera movement**

The speed of the robot, and thus the camera, is known to have only 3 states. The robot can be stopped, or can be moving in either direction (eg. at 8.6 m/min). This simplifies the process of tracking an object in multiple frames, as the distance travelled is known.

### 5.1.2.2 Target conformity

The targets are highly consistent in shape, size, intensity and orientation. The hens' eyes (when visible) appear as a dark circle (or ellipsoid) in a bright background area. The size varies only in relation to the position of the bird in the cage.

The image analysis of this application takes place in 3 discrete steps: pre-process, process and action.

### 5.1.3 Pre-process

The first task is to reduce the amount of processing required in subsequent steps. This is usually done by a combination of sub-sampling or data reduction. In this application, edge detection and intensity thresholding are performed to reduce the number of possible target areas. As seen in Figure 9 below, the image is reduced to a binary image displaying only the light/dark contrast areas.



**Figure 9. Representation of the image shown in Figure 7b after reduction to a binary image displaying only the light/dark contrast areas.**

#### Pseudo-code

For each pixel in the image:

    Determine edge value using Sobel Filter (size 10 pixels)

    If edge value >  $\text{Thresh}_{\text{edge}}$  and Intensity >  $\text{Thresh}_{\text{intensity}}$

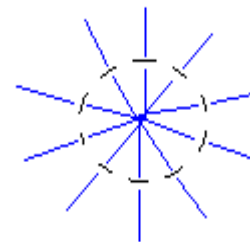
        Output Pixel = Target

    Otherwise

        Output Pixel = non Target

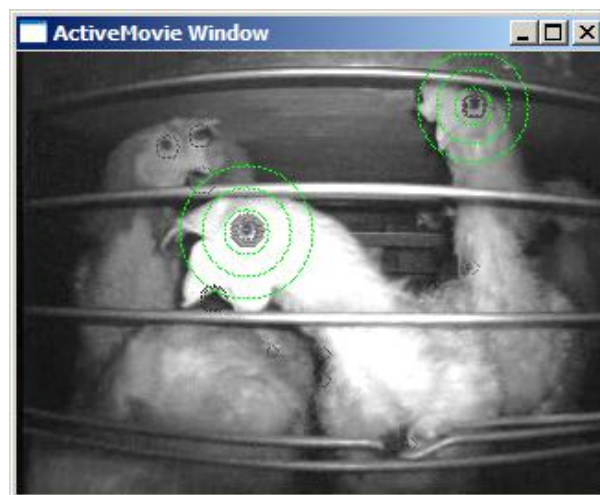
### 5.1.4 Process

The next step is to process the image for the existence of targets (eyes). This task is achieved using a Hough Transform for circle detection (Illingworth, 1988; Leavers, 1993). In essence, the Hough transformation accumulates a searchable parameter space of possible circles. The accumulation is acquired by each pixel ‘voting’ on possible circle existence from the state of that pixel. For example, a pixel not on an edge will not add to any accumulator, but an edge pixel will add to accumulators that are normal to the direction of the edge. Figure 10 below demonstrates the process. Each of the edge sections of the circle (black dashed lines) add to the parameter space (blue lines). It can be clearly seen that the maximum area in the parameter space is where the accumulators intersect, which is at the centre of the circle.



**Figure 10. An example of parameter space ‘voting’ or accumulation.**

Using this method on the pre-processed image gives a number of possible targets in the original image by searching for maxima in the parameter space. Figure 11 below is the end result of this process. Possible circles are shown in grey. A number of overlapping possibilities indicates the presence of a well-defined target and is displayed at the centre of green target marker circles.



**Figure 11. An example processed image displaying detected eye targets.**

### 5.1.5 Results of the eye scanning software

Ten video image frames were manually checked against the automatic detection algorithm. The results, which are collated in Table 3, show there was a low detection rate (*viz.* about 35%) due mainly to the size and texture of the target in respect to the rest of the image. There are many small, dark areas in the image that can cause false positives unless strict circularity is enforced. This reduces the

detection rate of marginally visible targets. The low detection rate, compounded with the earlier finding that only about 20% of the possible eyes were visible on an image, suggests that at least under the present method of scanning, the use of the eye to count hens in cages is not viable.

**Table 3. Comparison of the number of hen eyes visible to the human observer in 10 selected frames and the number of targets (eyes) detected by the eye-scan software. Also shown is the number of false positives detected by the software, that is eyes counted by the software that were not present.**

Frame number	Number of hen eyes visible in frame	Number of eyes detected	Number of false positives
1	3	2	0
2	3	1	2
3	0	0	0
4	2	1	0
5	1	1	0
6	4	1	1
7	4	0	0
8	1	1	0
9	5	1	0
10	5	2	0
<b>Total</b>	<b>28</b>	<b>10</b>	<b>3</b>
<b>Proportion</b>		<b>35.7%</b>	

## 5.2 Counting hens by leg

A second potential target for counting hens in cages was also investigated, involving counting the hens' legs. The legs are visible through the gap above the egg collection tray (ie. above the cage floor) and below the feed trough. The skin of the legs is highly reflective under IR illumination, while the background generally does not reflect light. The constraints detailed in Section 5.1.2 above also apply in this situation. As can be seen from Figure 12 opposite, the legs are visible, however there is limited contrast, due mainly to the reflection from metal in the foreground washing out the image.



**Figure 12. An example image displaying leg targets.**



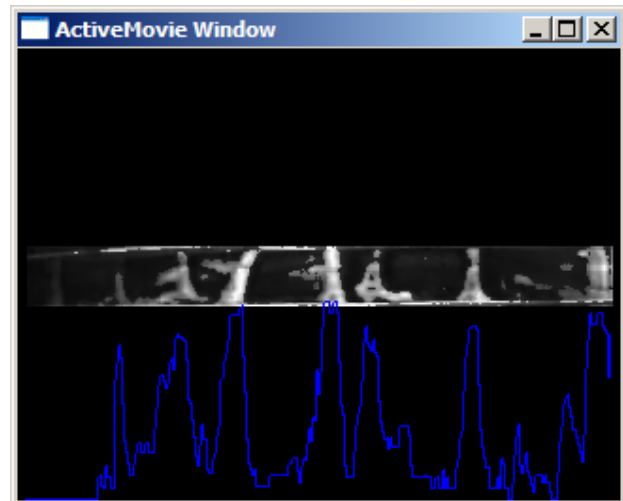
### 5.2.1 Process

Selecting the appropriate horizontal area in the image is a manual calibration that will be required for this algorithm. The area to investigate is in the centre of the screen, as shown in Figure 13.



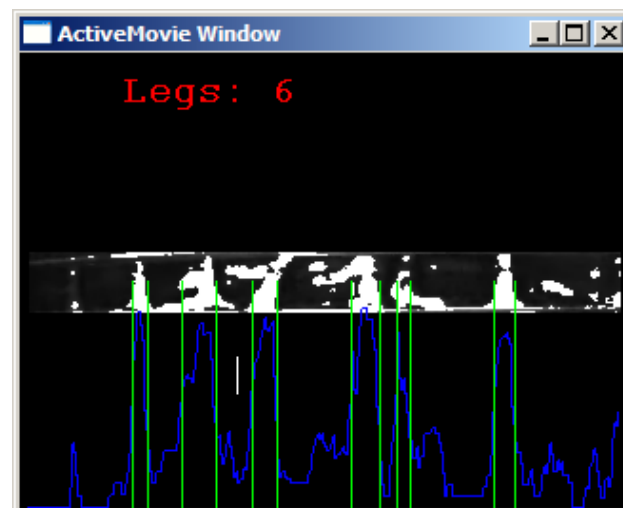
**Figure 13. An example image displaying the search space for the leg scan algorithm.**

In this region of the image all legs are seen as vertical (or almost vertical) stripes of higher intensity pixels. Accumulating a histogram of intensity for each column results in the histogram shown in blue in Figure 14.



**Figure 14. Intensity histogram overlaid onto the sample image.**

Thresholding the histogram then detects the presence of vertical bright strips (legs) in the image (Figure 15) and can be correlated to the number of live hens in the cage.



**Figure 15. Detected leg targets.**



### 5.2.2 Results of the leg scanning software

Observations from the eye scanning component of the project, reported in the previous section, suggested that there may be an opportunity to count the hens' legs in order to determine the number of birds in the cages. To evaluate the ability of the leg-scan software to detect hen legs, 20 image frames were selected from the digital video records from 4 cages in the upper tier of cages at DPI Werribee. Figure 3b shows the position of the camera used for video recording through the gap between the feed tray and the cage floor of the upper-tier cages. The number of birds per cage ranged from 4 to 8. The cages contained 'furniture' (ie. perch, nest box and dust bath), and as a result a bird's legs would be out-of-view if the bird was on the perch or in the nest box or dust bath. Five image frames were selected at random from the digital video records for each cage, and the 20 video image frames were manually checked against the automatic detection algorithm. Each frame selected per cage was taken from different passes of the robot and thus there is an assumption of temporal independence of the data. The results are collated in Table 4.

**Table 4. Comparison of the number of hen legs visible to the human observer in 20 selected frames and the number of targets (legs) detected by the leg-scan software. The number of false positives, that is legs counted by the software that were not present, is also shown.**

Frame	Number of legs visible <sup>†</sup>	Number of targets (legs) detected by software	Number of false positives
1	7	6	1
2	5	5	1
3	7	6	1
4	4	4	4
5	5	3	3
6	6	5	4
7	7	6	0
8	5	4	1
9	4	3	4
10	8	6	0
11	6	5	2
12	7	6	0
13	6	4	0
14	6	4	3
15	7	6	2
16	6	5	1
17	6	4	2
18	4	4	1
19	8	6	0
20	6	3	0
<b>Total</b>	<b>120</b>	<b>95</b>	<b>30</b>
<b>Proportion</b>		<b>79.2%</b>	<b>1.5</b>
Unit		% detection rate	Occurrence per cage

<sup>†</sup> Due to the cages containing a perch, nest box and dust bath, the legs of hens were not always visible, eg. if the hens were on the perch. Thus, the number of legs visible does not necessarily correspond to the number of birds per cage.

The leg-scan software detected about 79% of the legs visible to the human observer, with an average false positive rate of 1.5 legs per cage. The false positives could be reduced effectively by adding

some temporal position filtering into the process. By comparing the position of legs found each frame, spurious counts can be reduced dramatically.

There was a significant positive association (correlation analysis, Genstat 9.1) between the number of legs visible to the human observer and the number detected by the leg-scan software in the 20 cages ( $r = 0.78$ ,  $P < 0.001$ ). In addition, the number of false positives detected by the leg-scan software was inversely associated with the number of visible legs ( $r = -0.57$ ,  $P = 0.008$ ) and the number of legs detected by the leg-scan software ( $r = -0.44$ ,  $P = 0.05$ ).

Some issues affecting accuracy of the software detection were identified associated with:

- Birds in a squatting posture
- Birds in a standing posture with one leg raised
- Legs obscured by other birds
- Birds located at the rear of the cage with very low contrast between target and background
- Birds moving about in the cage
- The position of the camera relative to the egg collection tray

Thus there is the potential to further develop the use of legs as a means to count hens in cages, as viewed through the gap between the cage floor and the lower edge of the feed trough. Structural features of the cage front, in particular the position of the egg collection tray, limited the set up options for the miniature camera. With additional time for development, this limitation could be overcome. For example, by positioning the miniature camera within the egg tray space, while ensuring the eggs did not interfere with the camera, a superior view of the inside of the cage (and thus the legs) could be achieved. Moving the camera forward relative to the feed trough would also improve the video image by reducing the amount of reflectance into the camera from the front edge of the feed trough.

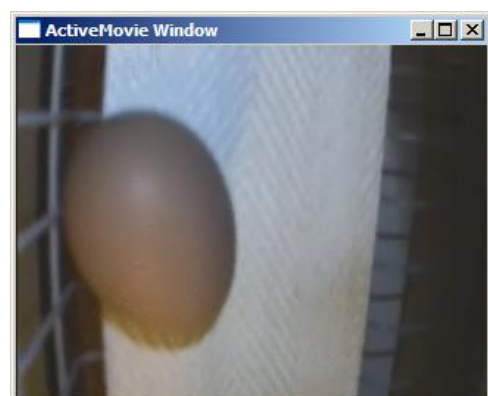
### 5.3 Egg belt blockage

The detection of blockages on the egg collection belt using VIA was approached in a similar manner to counting hens, as the low light level remains a major constraint. IR light, a low wattage white light source and the same source with blue gel filter were trialled. The combination of a miniature colour CCD camera (QC3468, Jaycar) and white light ('Mighty Bright Book Light') with blue filter (Rosco #3202, 'Full Blue', Rosco Gels) to illuminate the egg collection belt was superior to the miniature black and white CCD miniature camera with IR LED light source (QC3494, Jaycar) for the recognition of targets. The blue filter was added to the white light source to provide improved contrast between the brown eggs and the cream-coloured conveyor belt material (ie. the background). The VIA egg-scan software was developed to recognise various shapes in its catalogue. Non-egg shapes detected on the conveyor belt were recognised by the software as a 'foreign object'.

A standard set of egg images was investigated in the red-green-blue (RGB) space (Figure 16). The set of egg pixels were found to generally adhere to the relationship: Red intensity > Green intensity > Blue intensity. This provides a simple discrimination function that can be applied to determine target existence.

**Figure 16.** A sample original image of an egg on the egg collection belt at DPI Werribee.

#### 5.3.1 Pre-process



In the pre-process stage of this application, there are several tasks to accomplish. The extents (boundaries) of the egg belt should be determined periodically to account for image offsets. The direction of the camera should also be ascertained to assist in the localisation of any foreign objects that are found.

### 5.3.2 Egg belt extents

As the standard egg belt is a white material, this task is a simple matter of determining the extents of lighter material in the image.

#### Pseudo-code

For each column (vertical stripe) in the image

Determine the count of pixels  $> \text{Thresh}_{\text{intensity}}$

From the centre of the image find left and right extents of the histogram generated where count  $> \frac{1}{2}$  height.

Change the current extents 5% of the way towards the extents found in this process. This ensures that large, fast changes (from vibration or similar) do not cause inaccuracies.

The results of this process are displayed in Figure 17 as vertical blue lines. These extents are used as the limits in searching for eggs and foreign objects further in the processing.

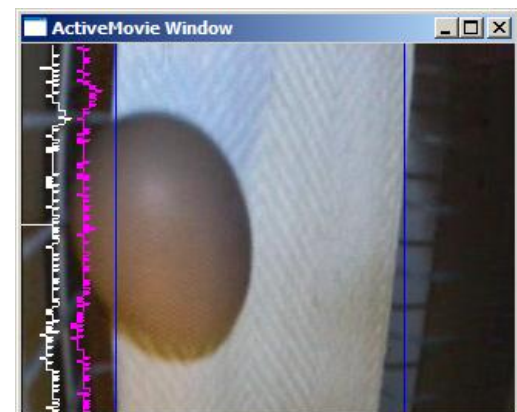


**Figure 17. Image of an egg on the egg belt with vertical blue lines that show the extents of the belt material detected by the software.**

### 5.3.3 Camera Speed

The camera speed can be determined by image registration between frames. As we know the egg belt will be moving vertically in the image (relative to the camera), we only need to search one dimension for the changes between frames. The simplest method of accomplishing this task is to sum the intensities of the pixels horizontally along each row into a histogram. As the image moves, the histogram will show a strong correlation at the offset relative to the number of pixels the image has moved.

For example, Figure 18 (opposite) displays the current frame histogram along the left side of the image in white, and the previous frame in purple. From this pair of histograms, the correlation was determined as -13, which means that the current image has moved down 13 pixels from the previous image.



**Figure 18. Image of an egg showing frame histograms on the left side of the image from the current (white) and previous (purple) image.**

### 5.3.4 Process

This stage has several distinct components. Initially, the position of any eggs must be determined. This is important as shadows cast by the eggs could easily be classified as foreign objects. Any other objects on the belt must then be detected and reported as foreign objects.

#### **5.3.4.1 Egg Detection**

Similar to the eye target detection, this process uses a Hough Transform to determine the presence of an egg in the image. While this method is effective, embedding the process onto a cheaper, embedded system will require changing to a different, more efficient technique such as s-psi coding (Dunn, 2007).

The Hough circle detection process is treated in the same manner as eye detection above, except that the radii of the circles the VIA software is searching for are much larger relative to the size of the image. This does not change the complexity of the task, but does introduce extra processing as the parameter space is increased. Figure 19 (opposite) displays an example image in gray scale representation of the target space.

**Figure 19. A example image in grey scale within the target space.**



After each edge pixel is added to the accumulators, the search of parameter space again yields the possible circles in the image, as shown in Figure 20 (opposite).

**Figure 20. Example showing an image in grey scale with accumulated target boundaries from targets detected in the previous few images.**

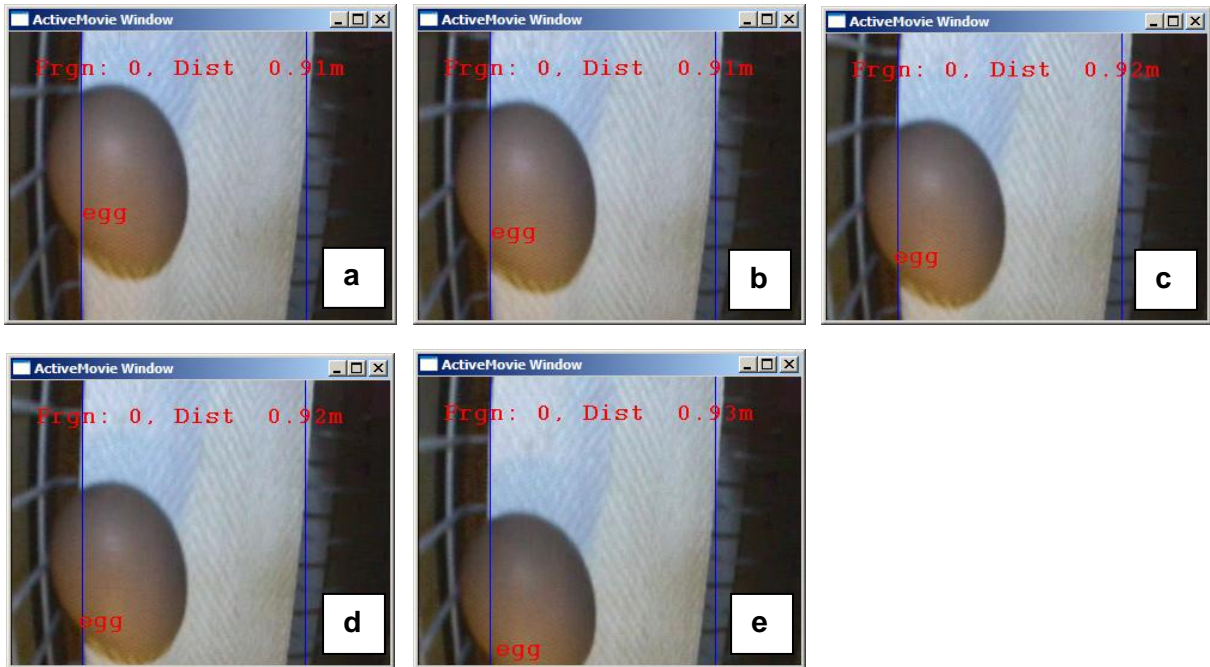


A threshold is set on the number of possible circles detected in the same area. If this threshold is reached, the object is classified as an egg and information registering its position is stored in a list for tracking in subsequent frames.

#### **5.3.4.2 Object tracking**

A process of tracking each detected egg until it passes out of the field of view is also required. This ensures that eggs detected in the centre of the image under optimal lighting conditions are not lost at the edge of the image and trigger false detection as a 'foreign object'.

As the speed the camera is travelling is known, the position of each previously detected egg can be updated at the commencement of each frame. This new, estimated position is then updated with the position of any actual egg found nearby. If no egg is detected, the estimated position is retained. Figures 21a-e display a sequence of video frames illustrating the object tracking process.



Figures 21a-e. A sequence of 5 video frames illustrating the object tracking process.

#### 5.3.4.3 Foreign objects

After eggs have been detected, anything else that is not similar to the belt colour/texture must be a foreign object. To remove variant illumination effects, this process is performed on a stripe in the centre of the image (Figure 22). As the robot is moving linearly, every part of the egg belt will be processed by this stripe. If there is an egg detected under the stripe, no further processing is undertaken on this frame.



Figure 22. Image showing the position of the black stripe in the centre of the image.

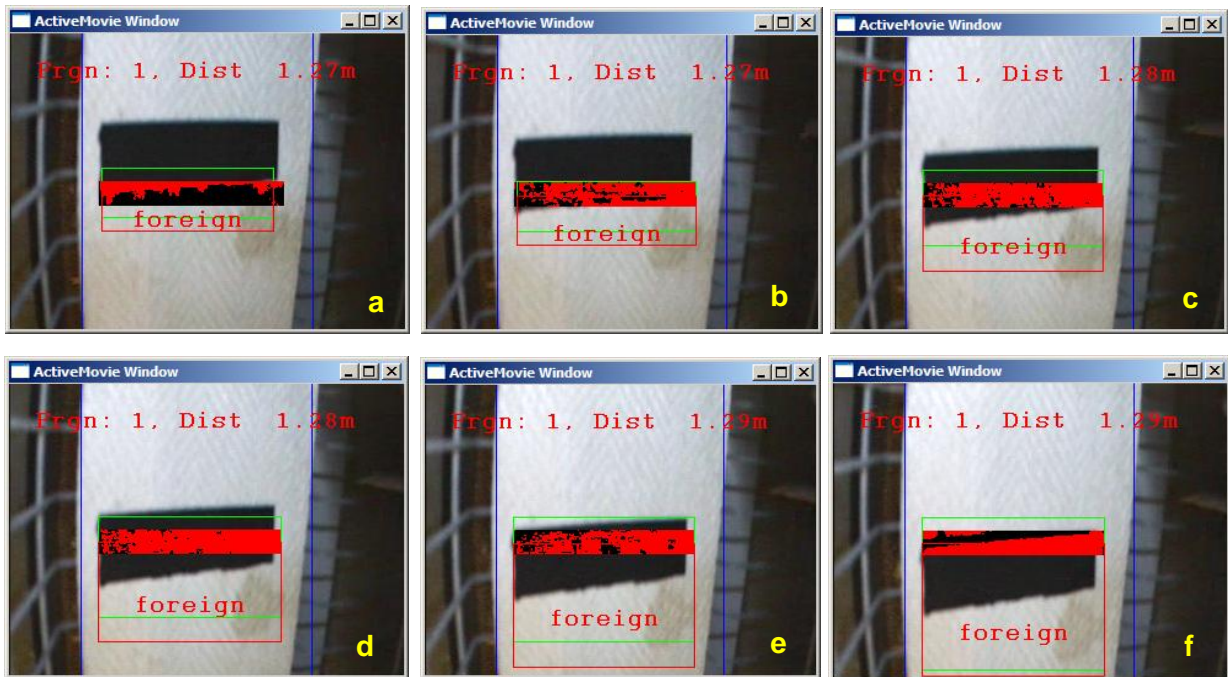
Figure 23 opposite displays some detected non-belt pixels (the boundary of the egg), but as an egg has been detected overlapping this area, it is correctly discounted from being a foreign object.



Figure 23. Image showing an egg entering the object detection area.



The following sequence of images (Figures 24a-f) illustrate the detection and tracking of a foreign object on the egg belt.

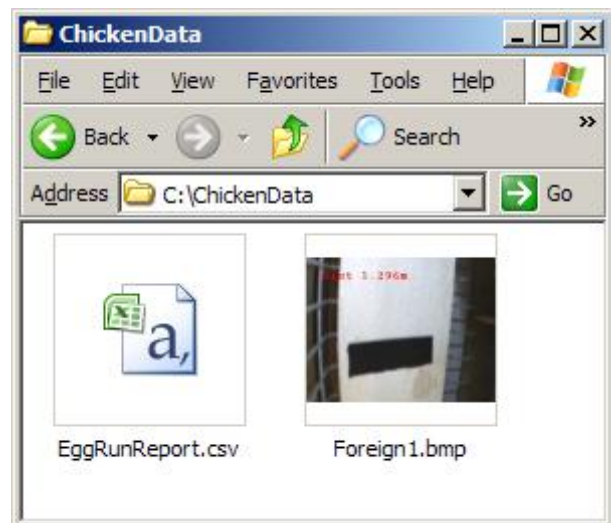


**Figures 24a-f.** Six images in a sequence illustrating the detection and tracking of a foreign object (a piece of black adhesive tape) on the egg belt.

#### 5.3.4.4 Action

The end result of this process for each scan of the egg belt is a report specifying the location of the possible blockage, along with a sample picture of the object posing the potential blockage. In this manner, the nature of the foreign object can be determined remotely and appropriate action taken. Figure 25 illustrates the result of the sample sequence of images above in Figures 24a-f. The foreign object has been correctly classified and is displayed in the report, along with the distance from the commencement of the egg belt.

**Figure 25.** Image showing the output display at the completion of a scan, with a pictorial representation of the detected foreign object (bmp file) and a record (csv file) of the position of the object detected from the start point of the scan.



### **5.3.5 Results of the egg belt scanning software**

The egg belt scan software was tested at both the DPI Werribee and the commercial farm. At both sites the detection rate of the ‘foreign objects’ was relatively high.

#### **5.3.5.1 DPI Werribee egg belt scans**

The egg belt trials at DPI Werribee involved 70 scans using the simulated robot and egg conveyor belt. Scans occurred in pairs, with the robot travelling first in one direction past the 5 cages, pausing for 1 min then returning back down the track. The length of egg belt scanned in each trial was about 6 m. Each of the 70 scans was recorded as a separate digital video file and analysed later using the egg-scan software to assess the accuracy of detecting eggs (either in singles and clusters) and foreign objects. For each pair of scans a predetermined number of eggs and foreign objects were placed on the egg collection belt. Eggs were positioned singly and in clusters of 2 to 6 eggs and the positions were predetermined by random selection. The different foreign objects and their position on the egg belt were also predetermined by random selection and between each pair of scans the objects on the egg belt were rearranged and/or replaced as required. The selection of foreign objects included the workers’ tools and hose fittings shown in Figure 26, as well as photographs of a hen’s head and leg/foot and a clump of feathers. The number of eggs and foreign objects per scan, along with the software analysis results from the scan, are shown in Appendix I.



**Figure 26.** The selection of worker’s tools used as foreign objects in the trial scans of the egg belt at DPI Werribee.

The summary information from the DPI Werribee egg-belt trial scans is shown in Table 5. On average, about 90% of foreign objects were detected on the egg belt in these scans. Interestingly, the foreign object detection rate was higher (93%) in tests in which the camera ‘followed’ rather than ‘preceded’ the robot (87%). The proportion of scans containing false negative(s) was also lower, but not significantly lower (Chi-squared test,  $\chi^2_1 = 1.45$ ;  $P > 0.05$ ) if the camera preceded (23.5%) rather than followed the robot (37.1%). The different foreign objects used in the DPI Werribee egg-belt scan trials, the number of times each object was used and the detection rate by the egg-belt scan software, are shown for each scan trial are shown in Appendix I. Three objects that the egg-belt scan software had most difficulty detecting were the electric light bulb, the roll of green-yellow striped electrical tape and the large blue-handled pliers. Images of these objects captured from the video records are presented in Figure 27. The images are paired to show scan events when the image was detected by the software and was not detected by the software. To the human eye the difference between the detected objects (true negatives) and the missed objects (false negatives) it is not evident. Further research to improve the scan process and refine the algorithms will improve the detection rate and reduce the incidence of false negatives.

**Table 5. The results from the egg collection belt scan trials at DPI Werribee. The camera was positioned on the right side of the robot (see Figure 3b) so that depending on the direction of movement by the robot, the video camera either ‘preceded’ or ‘followed’ the robot. The full details of individual scans are provided in Appendix I. There were 35 and 34 scans respectively, in which the camera preceded and followed the robot.**

Position of camera	Foreign objects on egg belt	Foreign objects counted (True negatives)	False negatives†	False positives†	Eggs on belt
Preceded robot	149	129 (86.6%)	20 (13.4%)	0	1,251
Followed robot ‡	144	134 (93.1%)	10 (6.9%)	3	1,215
<b>All trials</b>	<b>293</b>	<b>263</b> <b>(89.8%)</b>	<b>30</b> <b>(10.2%)</b>	<b>3</b> <b>(0.1%)</b>	<b>2,466</b>

† A ‘false negative’ was recorded when the software failed to detect a foreign object on the egg belt and a ‘false positive’ was recorded when the software recorded an egg as a foreign object.

‡ In scan #62 the digital video file did not record and no data were available for analysis.

The incidence of false positives, that is eggs recorded as foreign objects, was insignificant (0.1% of eggs). False positives are a minor concern as the output file displays a digital image of the ‘foreign object detected’ and the output report would show that the foreign object was an egg.



**Electric light bulb:**

**Trial 59      Detected**



**Trial 63      Not detected**



**Electrical tape roll:**

**Trial 17      Detected**



**Trial 17      Not detected**



**Blue-handled pliers:**

**Trial 16      Detected**



**Trial 15      Not detected**



**Figure 27. Example images from egg-belt scans at DPI Werribee of foreign objects that the egg-belt scan software detected and failed to detect. The figure shows three of the four foreign objects that were often missed by the software. Trial number indicates the scan trial from which the image was captured (see Appendix I).**

### 5.3.5.2 Kinross Farm egg belt scans

The results of the commercial farm egg-belt scan trials are shown in Table 6. Twenty scan trials were conducted and overall 95% of the foreign objects were detected. The first 10 scans occurred in cage row 2 and the last 10 scans occurred in cage row 8. In both sets of trials the third tier of cages from the bottom were used. Fourteen foreign objects and 260 eggs were placed on the 18 m (25 cage fronts) of the egg belt scanned per trial. Between each scan trial, the location and the orientation of ten of the 14 objects were re-randomised. The objects were hen legs, wings and head/neck, typical of the most likely objects (ie. a dead hen) found on the belt. The other four foreign objects were a hand saw and three pieces of black adhesive tape. The orientation of the hand saw was rotated through 180° after 5 trials on each cage row, while the 3 pieces of adhesive tape were not moved between trials.

**Table 6. The results from 20 scans of egg collection belts at Kinross Farm. The video camera was positioned on the right side of the robot (see Figure 5). Thus, for odd-numbered scans the video camera trailed the robot whereas for even-numbered runs the video camera preceded the robot. A ‘false negative’ was recorded when the software failed to detect a foreign object on the egg belt and a ‘false positive’ was recorded when the software recorded an egg as a foreign object.**

<b>Trial</b>	<b>Foreign objects on egg belt</b>	<b>Foreign objects counted</b>	<b>Duplicates†</b>	<b>False negatives</b>	<b>False positives</b>	<b>Eggs on belt</b>	<b>Missed details</b>
1	14	13	5	1	0	260	1 leg
2	14	14	3	0	3	260	
3	14	14	4	0	2	260	
4	14	14	6	0	1	260	
5	14	14	8	0	1	260	
6	14	14	7	0	1	260	
7	14	13	7	1	2	260	1 leg
8	14	13	5	1	1	260	1 leg
9	14	13	8	1	1	260	1 leg
10	14	14	7	0	1	260	
11	12	10	2	2	2	260	2 legs
12	14	14	3	0	3	260	
13	14	13	1	1	1	260	1 leg
14	14	13	3	1	3	260	1 leg
15	14	14	4	0	1	260	
16	14	12	3	2	1	260	2 legs
17	14	14	4	0	0	260	
18	14	14	4	0	1	260	
19	14	11	5	3	0	260	3 legs
20	14	14	5	0	0	260	
<b>Total</b>	<b>278</b>	<b>265</b>	<b>94</b>	<b>13</b>	<b>25</b>	<b>5200</b>	
<b>%</b>		<b>95.3%</b>		<b>4.7%</b>	<b>0.48%</b>		

† Duplicates – more than one bitmap of the same foreign object was captured in the particular scan.

**Trial 1:**

**Detected**



**Not detected**



**Trial 7:**

**Detected**



**Not detected**



**Trial 8:**

**Detected**



**Not detected**



**Trial 9:**

**Detected**



**Not detected**



**Figure 28. Comparative examples from 4 scan trials using the egg-belt scan software in which the software detected (left images) and failed to detect (right images) hen legs on the egg belt.**

As shown in Table 6, hen legs were the only object not detected by the belt-scan software. Example images of legs detected and not detected by the egg-belt scan software are shown in Figure 28. It is not immediately apparent to the human observer why some legs were not detected. However, as mentioned in the earlier section regarding foreign objects missed by the VIA software in the DPI Werribee trials, with additional research on the set-up of the prototype system and further refinement of the algorithms, the detection rate will be further improved.

## 5.4 Detecting ‘dead’ hens in cages

As there was some inconsistency in counting hens reliably using the leg-detection techniques (the eye-count aspect was too unreliable to pursue), we considered a third option during the commercial farm component of the project. Rather than count the number of hens, we considered an alternative possibility of trying to detect dead hens in the gap between the cage floor and the feed trough. In the event that a hen dies, it is likely that due to the slope of the floor the body gravitates towards, and eventually rests against, the front of the cage. In this situation, the other birds may stand on the dead bird, pushing it through the gap between the cage floor and the bottom of the feeder. Undetected dead birds are thus a real risk cause a blockage off the egg collection belt. Further, with the deceased hen in this position, the legs of the other hens would not be in the field of view when the feeding robot passed the cage. Instead, there would be a feathered body in the field of view. The detection of the latter could indicate that a hen was dead in a cage. The third consideration therefore was to determine whether the VIA software could detect a mass of feathers (ie. a body of a hen) in the gap between the cage floor and the lower edge of the feeding trough.

Digital video clips were captured using the DPI Werribee robot with a camera positioned for scanning the legs of hens. A ‘simulated’ dead hen, made from feathers attached to a cardboard shape, was placed in the gap between the cage floor and the lower edge of the feed trough in the upper-level tier of cages. The video clips were examined by the software programmer and algorithms to recognise the ‘simulated’ were generated. Based on the data available, the up graded leg-scan software was able to detect the ‘simulated’ dead hen. Further trials are required to refine and test the efficacy of the software. This could be conducted in the post-project period should the Poultry CRC which to progress this aspect. The up-graded software should therefore enable the detection of dead hens as well as counting the number of hen legs per cage.

## 6 Discussion of Results

The objectives of the proposed research project were to test the proof of concept that automatic video image analysis (ie. machine vision) could be used to 1) count live laying hens in cages and 2) identify egg belt blockage.

The project demonstrated that ‘machine vision’ or automatic video image analysis (VIA) could be used to count hens in cages and to monitor the egg collection belt to detect obstructions. Counting hens in cages was considered as a first step in being able to monitor hens automatically leading to a mechanism for automatic monitoring of bird welfare and health. Monitoring the egg collection belt to detect potential blockages would provide an automatic alert system to detect risk situations that may result in increased incidence of cracked and broken eggs. In the project, robotic feeding machines were used to transport miniature cameras along the rows of cages to permit the application of VIA.

Two prototype machine vision systems were developed to count hens in cages utilising two targets on the birds (eyes and legs). Only the leg-target however, showed potential for counting hens in cages. The ‘leg-scan’ software detected 79% of visible legs in our evaluation trials. However, better positioning of the camera would greatly improve the detection rate.

The project also successfully developed a prototype to detect potential blockages on the egg collection belt. The ‘egg-belt scan’ software detected between 90 and 95% of foreign objects, that is non-egg objects. Further refinement of the software will improve the detection rate.

In addition, the opportunity exists to refine the ‘leg-scan’ software further to detect dead hens inside cages. Dead hens appeared to be one of the main causes of egg belt blockage at the commercial farm, and thus by addition this component of the software, the accuracy of the egg-belt scan software should be further improved.

The project proves the concept that VIA can be applied to count hens and monitor egg belts in a modern cage egg production system. The two variations of VIA software developed, ‘leg-scan’ and ‘egg-belt scan’, have genuine practical application. The knowledge gained in this project will also assist the use of the technology in other livestock situations. Probably the biggest factor limiting the further application of the technology is one’s own imagination.

## 7 Implications

The modern cage egg industry, with its use of various mechanical devices for robotic feeding, egg collection and manure collection, is the most likely to benefit from this project in the short term as the applications we tested are current issues for that industry. In Australia there are about 5.44 million laying hens in this component of the egg industry, producing about 35% of Australia’s eggs with an estimated value of production of AUD \$100 million annually. The minimum flock size on farms that have invested in the automated (robotic) technology is likely to be in the order of 100,000 hens. In Victoria there are probably 10 farms in this category and across Australia the estimate is 61 farms (personal communication, Geof Runge).

Mr Philip Szepe (Kinross Farms, Kinglake West, Victoria) estimated the cost of stockperson labour to be \$0.04 per dozen eggs for an automated cage egg production enterprise. This estimate is based on a ratio of 1 stockperson to 70,000 birds, with the stockperson working a 56 hour week (ie. 7 days). About 50% of the stockperson time is accounted for by direct checks on the birds. The remaining labour costs are associated with stockperson activities particularly associated with cleaning, checking and maintenance of equipment in and around the sheds. The activities of the stockpeople also include checking the egg collection belts to avoid the occurrence of blockages that lead to egg breakages. Despite the stockpeople checking the belts before the collection of eggs, Mr Szepe acknowledged that egg belt blockages still occur, with probably one “major mess” occurring weekly on his farm.

This project successfully tested the concept that machine vision can be applied to cage egg farms. Following further refinement, the technology should provide economic and social benefits for stockpeople and producers. Economic benefits will occur through reduced labour inputs per unit (eg. per cage of birds or per shed) and reduced egg wastage, which should result in savings to the producer and increase profits. Stockpeople will be able focus their time dealing with higher priority work tasks, as they spend less time performing ‘unprofitable’ activities that would be monitored automatically

using the machine vision technology. The social benefits for egg producers are probably less tangible but may include the benefits of increased stockperson retention. Stockperson retention may increase due to improved job satisfaction. Governments and the public will have increased confidence that the welfare of hens is better monitored through increased frequency of inspection.

It is anticipated that these technologies, once developed, could be commercially manufactured either for new systems or appended to existing robotic systems within 3 to 5 years.

## 8 Recommendations

It is recommended that the Australian Poultry CRC discusses these results with relevant cage manufacturers / suppliers, with the view to commercialisation.

Further research is required to:

1. refine the leg-scan and egg-belt scan prototypes and software, as this will result in improvement to the detection rates achieved in this proof of concept project, and
2. refine a finding of the project to recognise dead hens in cages.

## 9 Acknowledgements

I am extremely grateful to all the people who contributed to this project. To Philip Szepe, for providing us access to Kinross Farm enabling us to conduct the on-farm component, and to the farm manager and stockpeople at Kinross Farm for their friendly assistance and patience with us during that component of the work. To Samantha Borg, Senior Technical Officer, DPI Werribee, I am very appreciative of for her technical and organisational skills that ensured the robots, the computers and the video equipment behaved themselves, and for conducting most of the hands-on trial work conducted within the project. The poultry at DPI Werribee were expertly cared for by Samantha Borg, Bruce Schirmer and Tracie Storey.

This project would not have been possible without the combined expertise in engineering, computer hardware and software, and photography, brought to the project by Mark Dunn from the National Centre for Engineering in Agriculture, University of Southern Queensland (Toowoomba, Queensland) and John McPherson (A Vision Fantastic, Hoppers Crossing, Victoria).

The encouragement and support of Dr John Barnett (Animal Welfare Science Centre, DPI Werribee and Poultry CRC Sub-program Manager) and Dr Jenny Sexton (DPI Victoria, Program 6.1 Key Project Manager) is gratefully acknowledged. I am also indebted to John Barnett for reading and commenting on this Final Report.

I am very appreciative of the Poultry CRC and DPI Victoria, Program 6, for co-funding this proof of concept project.

## 10 Glossary

CCD	Charge coupled device; a solid-state imaging device
IR	Infra-red light at a wavelength longer than red (840 nm-1000 nm)
LED	Light emitting diode
RGB	Red, green, blue (wavelengths)
USDA	United States Department of Agriculture
VIA	Video image analysis

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## 12 Appendices

### Appendix I - Full data from Werribee egg belt scans

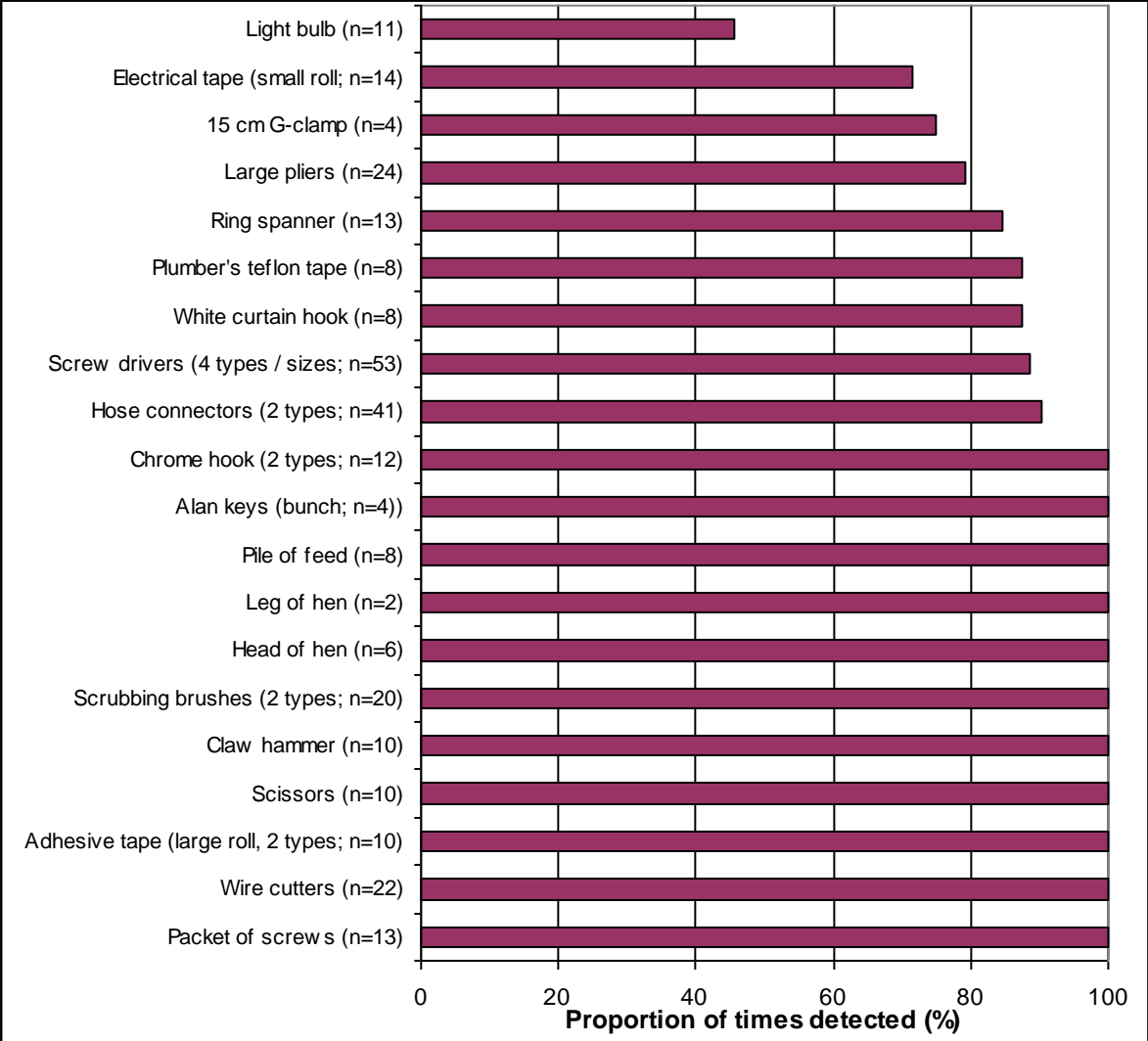
Trial	Foreign objects	Foreign objects detected	False negatives	False positives	Eggs	Missed details
1	5	5	0	0	35	
2	5	5	0	0	35	
3	5	5	0	0	35	
4†	4	4	0	0	35	
5	5	3	2	0	35	2 screwdrivers
6	5	5	0	0	35	
7	5	5	0	0	35	
8	5	4	1	0	35	Large screwdriver
9	3	3	0	0	37	
10	3	2	1	1	37	G-clamp & 2 eggs clumped
11	3	3	0	0	37	
12	3	3	0	0	37	
13	4	4	0	0	36	
14	4	4	0	0	36	
15	4	3	1	0	36	Pliers
16	4	4	0	0	36	
17	5	4	1	0	35	Electrical tape roll
18	5	5	0	0	35	
19	5	4	1	0	35	Pliers
20	5	4	1	0	35	Pliers
21	4	4	0	0	36	
22	4	2	2	1	36	Electrical tape roll & Hose connector
23	4	4	0	0	36	
24	4	4	0	0	36	
25	5	4	1	0	35	Hose connector
26	5	5	0	0	35	
27	5	5	0	0	35	
28	5	4	1	1	35	Spanner
29	3	3	0	0	37	
30	3	3	0	0	37	
31	4	4	0	0	36	
32	4	4	0	0	36	
33	4	4	0	0	36	
34	4	4	0	0	36	
35	4	3	1	0	36	Spanner
36	4	4	0	0	36	
37	4	4	0	0	36	
38	4	4	0	0	36	
39	4	4	0	0	36	
40	4	4	0	0	36	

*Continued on next page*

† In the period between scan #3 and #4, the hens removed one foreign object from the egg belt.

Trial	Foreign objects	Foreign objects detected	False negatives	False positives	Eggs	Missed details
<i>Continued from previous page</i>						
41	4	4	0	0	36	
42	4	4	0	0	36	
43	4	3	1	0	36	Light bulb
44	4	3	1	0	36	Orange hose connector
45	4	3	1	0	36	Light bulb
46	4	4	0	0	36	
47	5	5	0	0	35	
48	5	5	0	0	35	
49	5	5	0	0	35	
50	5	4	1	0	35	White hook
51	4	4	0	0	36	
52	4	4	0	0	36	
53	4	4	0	0	36	
54	4	4	0	0	36	
55	4	3	1	0	36	Teflon tape roll
56	4	4	0	0	36	
57	4	4	0	0	36	
58	4	4	0	0	36	
59	4	2	2	0	36	Black hose connector & Light bulb
60	4	4	0	0	36	
61	4	4	0	0	36	
62	-	-	-	-	-	AVI file did not record
63	4	1	3	0	36	Pliers, Screwdriver & Light bulb
64	4	4	0	0	36	
65	4	0	4	0	36	Electrical tape roll, Pliers, Screwdriver & Light bulb
66	4	2	2	0	36	Electrical tape roll & Light bulb
67	5	5	0	0	35	
68	5	5	0	0	35	
69	5	4	1	0	35	Short screwdriver
70	5	5	0	0	35	
<b>Total</b>	<b>293</b>	<b>263</b>	<b>30</b>	<b>3</b>	<b>2,466</b>	
		<b>(89.8%)</b>	<b>(10.2%)</b>	<b>(0.12%)</b>		

**Appendix I (cont). Foreign objects used in the DPI Werribee egg-belt scan trials in order of least (top) to most (bottom) detected by the software.**



## Appendix II - Software installation instructions



# Installation Instructions

This software is designed as a prototype machine vision system to accompany the research results from Project CRC 06-11, which was funded jointly between the Australian Poultry CRC and DPI Victoria.

Project CRC 06-11 was a one-year proof of concept project to determine whether machine vision technology could be applied to the cage egg industry.

The project tested the concept that machine vision can be used to:

1. count the number of live hens per cage (with multiple hens per cage), within a row of cages, and
2. identify potential blockages of the egg conveyor belt that may result in damaged eggs

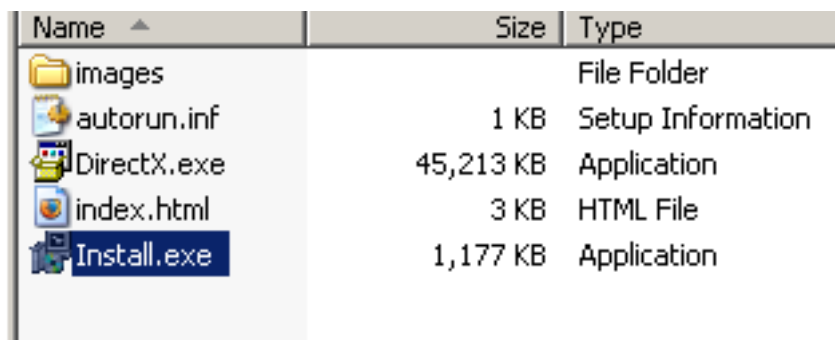
[Setting up software](#)

[Setting up DirectX](#)

[Running the Program](#)

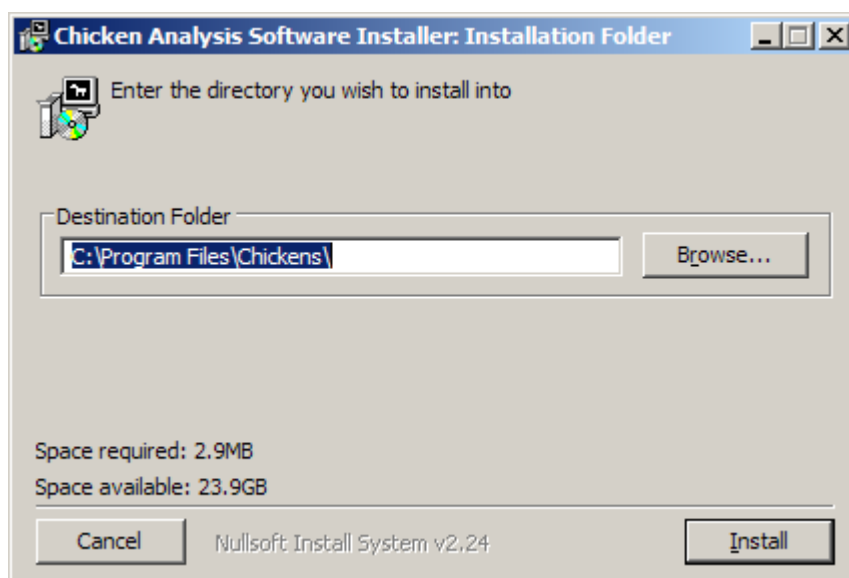
## To setup included software:

1. Insert the CD into the PC.
2. The installer should start automatically. If it does not, open up Windows Explorer, and navigate to the CD/DVD drive. Double-click on "Install.exe" in the base directory of that drive.

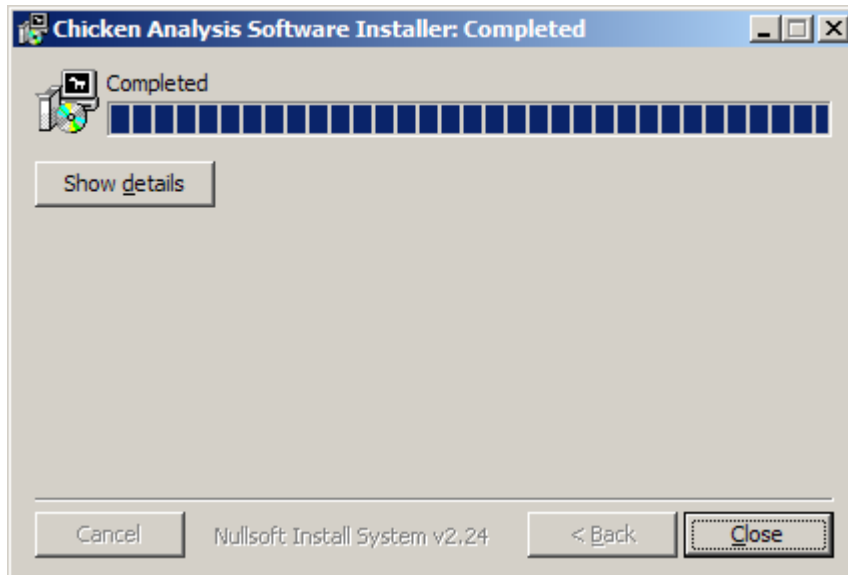


Name	Size	Type
images		File Folder
autorun.inf	1 KB	Setup Information
DirectX.exe	45,213 KB	Application
index.html	3 KB	HTML File
Install.exe	1,177 KB	Application

3. The installer will ask for a destination directory. If you wish, you can select a more favourable directory to install to. Once selected, click the "Install" button in the lower right corner of the window to continue.



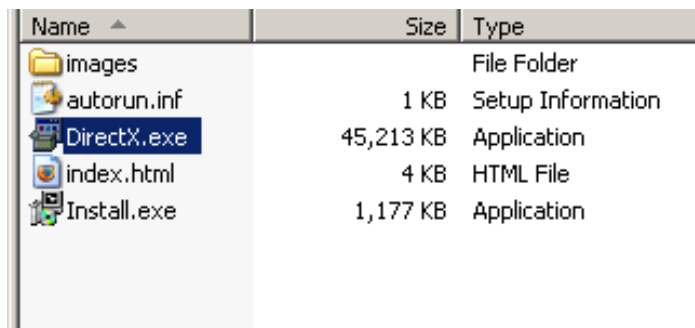
4. A progress bar should display the installation progress. After the bar has reached the end, the "close" button at the lower right corner of the window will be enabled. Click it to complete installation.



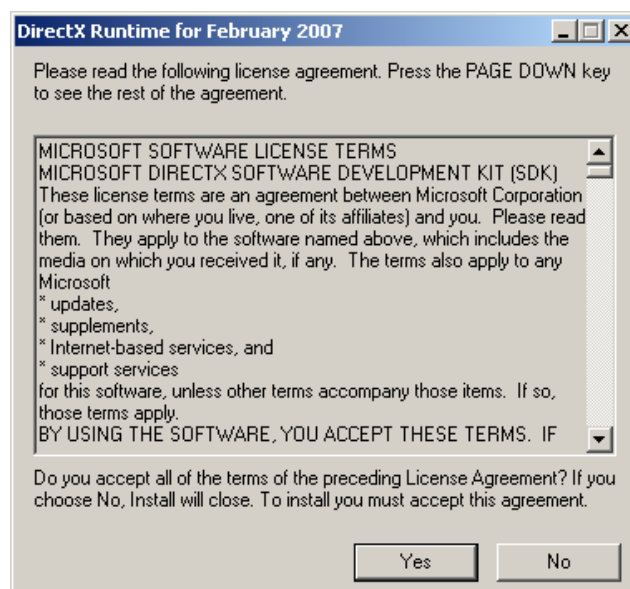
5. This software requires DirectX 8.0 or higher libraries. If they are not installed on the computer, the installation software will inform you to install DirectX before continuing. If this is the case, follow the instructions in the section labeled "Installing DirectX", then restart the installation process from the beginning.
6. Once the software has been installed, an icon on the desktop and in the start menu should appear.

## Installing DirectX:

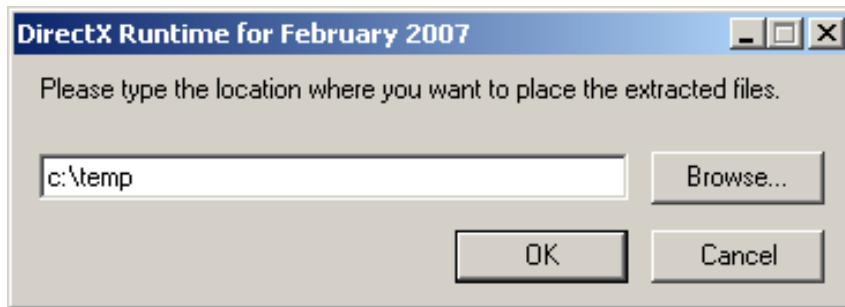
1. This is only necessary if you don't have version 8.0 or later of DirectX installed on the PC. To check, run the installer above, and it will indicate if DirectX needs to be installed on the PC. Note that it is OK to reinstall DirectX from any version if the software detects the incorrect version or if problems are encountered.
2. To install DirectX, open up Windows Explorer, and navigate to the CD/DVD drive. Double-click on "DirectX.exe" in the base directory.



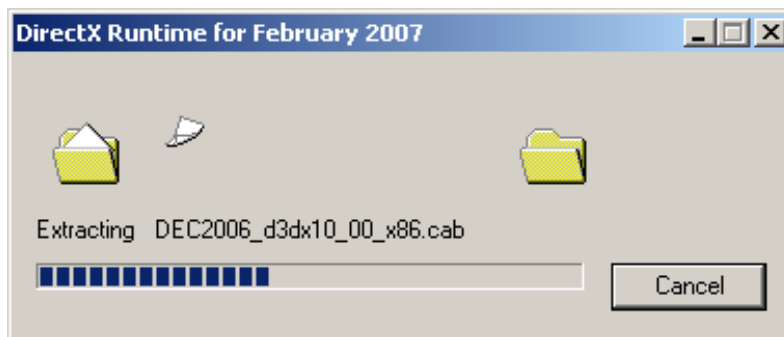
3. Press "Yes" to accept the license agreement and continue.



4. Choose an appropriate location for the temporary files. If unsure, type "c:\temp" in the text area. Press "OK" to continue.



5. The program will then copy many files to that location. This may take some time, so be patient. Once this is done, the program will exit (and the window will disappear).

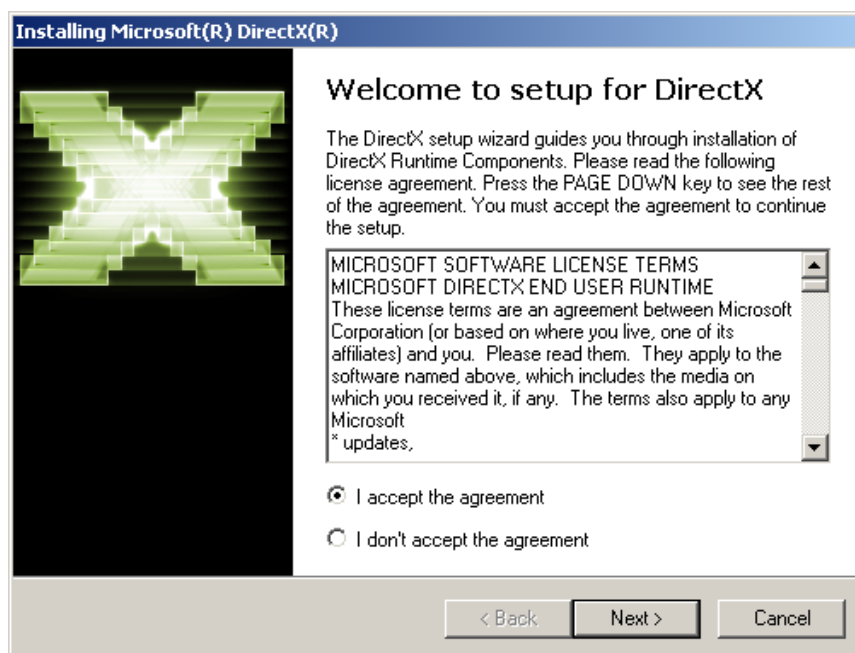


6. Open up Windows Explorer again (or use the same window if you wish), and navigate to directory you specified (such as "c:\temp" in our example). Double-click on "DXSETUP.exe".

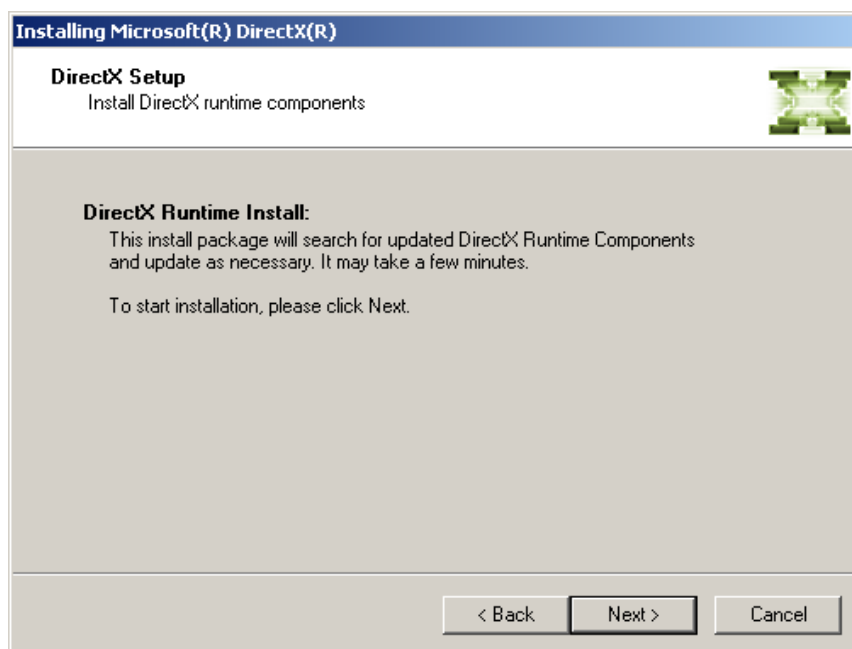
Name	Size	Type
DSETUP.dll	76 KB	Application Extension
dxdllreg_x86.cab	45 KB	Cabinet File
dxnt.cab	12,955 KB	Cabinet File
DXSETUP.exe	492 KB	Application
dxupdate.cab	84 KB	Cabinet File
Feb2005_d3dx9_24_x64.cab	1,220 KB	Cabinet File
Feb2005_d3dx9_24_x86.cab	991 KB	Cabinet File
Feb2006_d3dx9_29_x64.cab	1,332 KB	Cabinet File
Feb2006_d3dx9_29_x86.cab	1,061 KB	Cabinet File
Feb2006_VACT_x64.cab	176 KB	Cabinet File



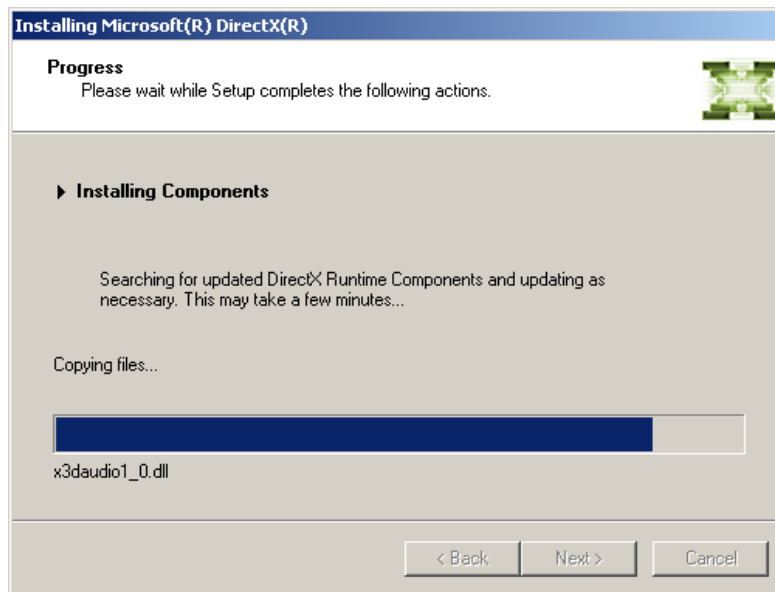
7. Click on the radio button next to "I accept the agreement" to indicate you do accept the agreement, and press "Next" to continue.



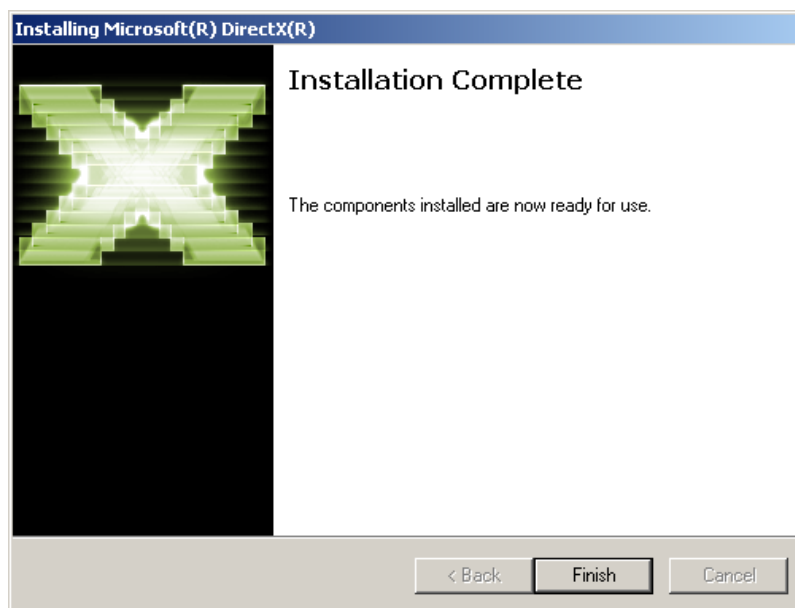
8. Press "next" to start the DirectX install process.



9. The DirectX installer will now install onto the PC. This may take a long time, so be patient.



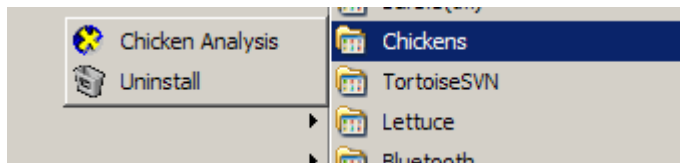
10. The program will then display a message indicating that it installed correctly. If it displays different text asking to save your work first, this indicates that it will automatically restart the PC when the program closes. Press "Finish" to close the program.



## Running the program

The algorithms may be run either live from a camera or image capture device plugged into the computer, or against a previously recorded file.

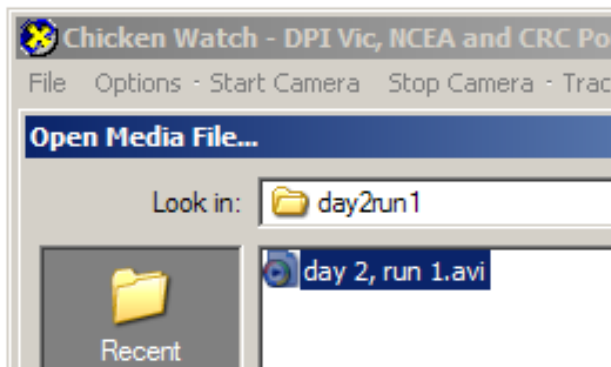
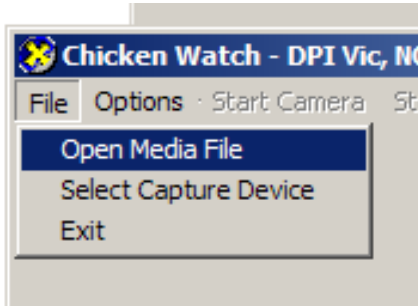
1. To start up the chicken analysis program, run "Chicken Analysis" in the "Chicken" section from the Start menu.



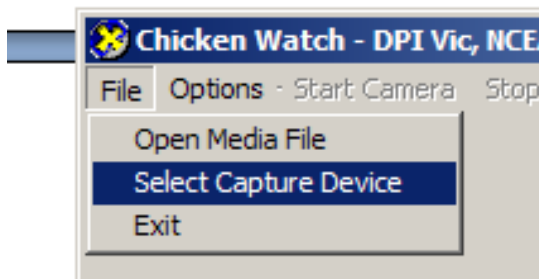
2. The main window will then be displayed. The main action menu is along the top.



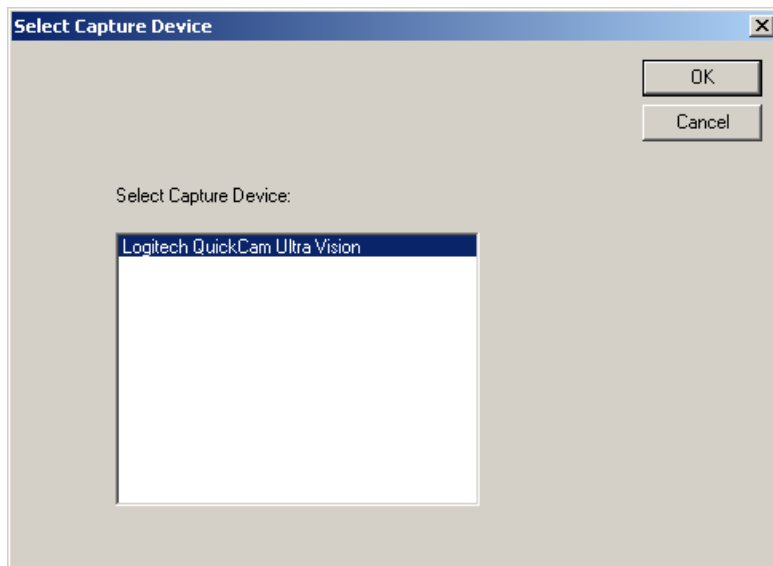
3. If you wish to use a pre-recorded image file, click on the "File" menu, and select "Open Media File". Then, navigate to the correct file, and press "open".



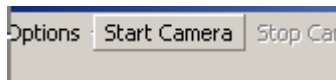
4. To instead use images directly from an attached camera, press File -> Select Capture Device.



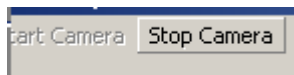
5. Select the appropriate image capture device from the list and hit 'OK'



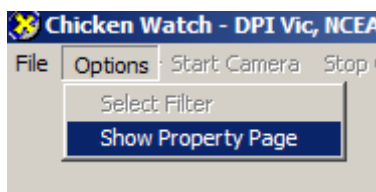
6. Then press "Start Camera".



7. When the image analysis process is complete, simply click "Stop Camera", or exit the program.

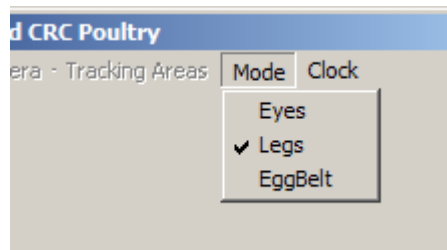


8. If you wish to change the camera properties (such as the brightness), click on the "Options" menu, and select "Show property page".



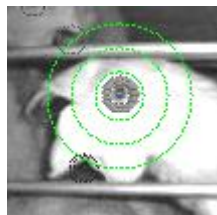
## Selecting Algorithms

The 'mode' option on the menu bar allows the user to switch between algorithms



## Eyes

The eye algorithm is used to automatically detect and log the number of eyes in each frame of video as the robotic feeder progresses down the shed. An example image is shown below.



The darker target of the non-IR reflecting eye is seen here circled. The count of the number of eyes found in each cage is logged to the file:

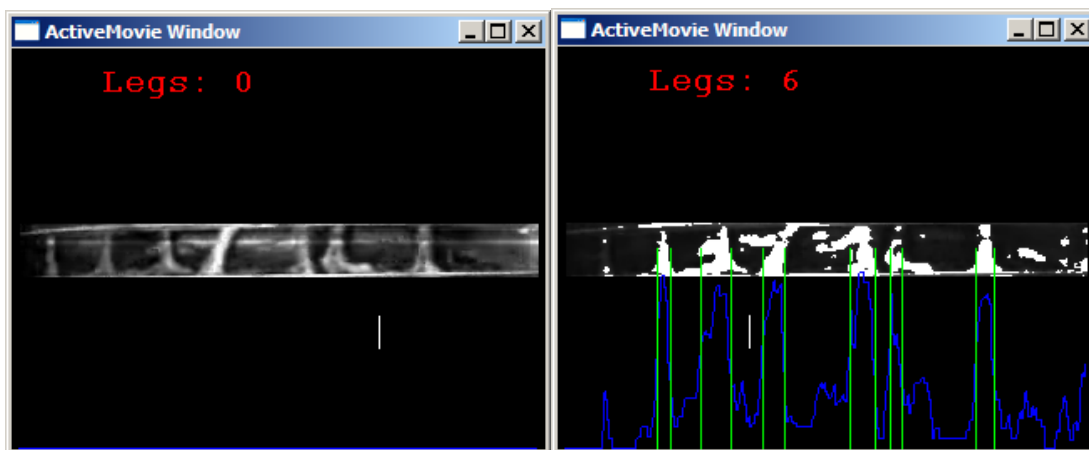
'C:\ChickenData\EyeRunReport.csv'

Each line of the result file contains the distance, and the x and y coordinate of where each eye was found. From this data, further processing may resolve estimated number of hens at each distance in the run.

## Legs

The leg algorithm is an additional algorithm to detect and count hens in each video sequence. In this algorithm, the camera is focussed under the feed tray and above the egg belt. There should be enough light to illuminate to the back of the cages without overexposure from reflections above and below the target area.

The images below are an example original and processed frame from a video sequence.



This process logs to the file:

`'C:\ChickenData\LegRunReport.csv'`

Each line of the results file contains the distance and one x coordinate for each leg detected in the image. The data can again be post-processed for additional information.

## Egg Belt

The egg belt process is specifically targeted at detecting foreign objects on the egg belt that may cause a blockage. In this process, the camera is located above the egg belt, focused downwards with a blue light beside the camera illuminating the scene. The blue light adds contrast between the eggs and the generally white egg belt.

The image below is a sample frame from this process.



For calibration purposes, an egg may be placed centrally under the camera. The illumination source may then be adjusted until the target is recognised as an egg (text will be overlaid onto the image). When a foreign object is detected, the algorithm checks that it is not an egg shadow, and then logs the occurrence.

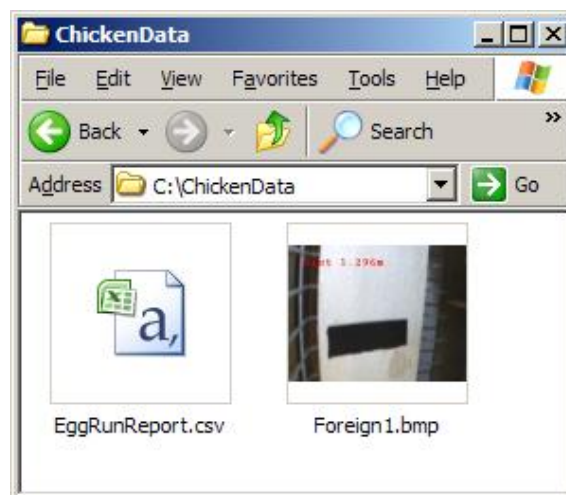




This process logs to the file

‘C:\ChickenData\EggRunReport.csv’

Each record contains the start and end distance of the foreign object. A picture of the object is also recorded as a bitmap in the ‘C:\ChickenData’ directory. The name of the file recorded will be Foreign*i*.bmp (where *i* is the count of foreign objects found so far. Note that these files will be overwritten if the process is restarted.



## Plain English Compendium Summary

<b>Project Title:</b>	Using machine vision to count hens and reduce egg breakage – proof of concept.
Project No.:	CRC 06-11
Researcher:	Dr Greg Cronin
Organisation:	Department of Primary Industries, Victoria
Phone:	03 9742 0450
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Email:	<a href="mailto:greg.cronin@dpi.vic.gov.au">greg.cronin@dpi.vic.gov.au</a>
<b>Objectives</b>	The project tested the proof of concept that automatic video image analysis (ie. machine vision) could be used to 1) count live laying hens in cages and 2) identify egg belt blockage.
<b>Background</b>	Machine vision, or automatic video image analysis, is a technology that enables computers to “see”. A camera is connected to a computer containing appropriate software, which enables the computer to recognise objects. Depending on the software, decision-making logic can be applied in the absence of humans. Thus the technology provides the opportunity to replace humans in the performance of certain mundane, repetitive or difficult tasks that require decision-making, and to perform the tasks at greater speed and with lower error rates. This project examined whether two prototype machine vision systems could be developed and applied to the cage egg industry. The systems involved counting hens in cages and detecting objects on the egg conveyor belt that might block the movement of eggs and cause breakage and waste of eggs. The ability to count hens is considered a first step in providing a computerised mechanism for the automatic monitoring of bird health and welfare. In addition, the mechanical nature of the system allows for the frequency of monitoring to be greatly increased compared to manual monitoring, and the logical decision-making aspect ensures objective monitoring occurs. For example, the computer would not miss a problem due to “human error”.
<b>Research</b>	The research was conducted at DPI Werribee and on a commercial cage egg farm. Video cameras were attached to mechanical feeding robots that delivered feed to the feed troughs in front of the hens’ cages. This provided the means to transport the cameras along the front of the cages. Video image analysis software was developed to detect selected targets

	<p>that were used to identify and count birds inside the cages or foreign objects on the egg collection belts. As the one-year project progressed, the prototypes including the software were refined to improve the rate of target detection.</p>
<b>Outcomes</b>	<p>Two prototype machine vision systems were developed and evaluated. Counting hens in cages had a 79% accuracy, while over 90% of foreign objects were detected on the egg collection belt. Accuracy is likely to improve with further research and commercialisation.</p>
<b>Implications</b>	<p>The modern cage egg industry, with its use of various mechanical devices for robotic feeding, egg collection and manure collection, should benefit from this project. In Australia there are about 5.44 million laying hens in the cage egg industry, producing about 35% of Australia’s eggs with an estimated value of production of AUD \$100 million annually. The minimum flock size on farms that have invested in the robotic technology is likely to be in the order of 100,000 hens. In Victoria there are probably 10 farms in this category while across Australia the estimate is 61 farms.</p> <p>About 50% of the stockperson’s time is accounted for by direct checks on the birds. The remaining labour costs are associated with stockperson activities particularly associated with cleaning, checking and maintenance of equipment in and around the sheds. The activities of the stockpeople also include checking the egg collection belts to avoid the occurrence of blockages that lead to egg breakages. Despite the stockpeople checking the belts before the collection of eggs, egg belt blockages still occur. The use of multi-tier cage systems, with many birds and egg collection belts located above eye-level of the stockperson, increases the difficulty for the stockperson checking cages and egg belts, and increases the risk that sick birds and potential blockages of the egg belt are not detected until after an adverse event occurs.</p> <p>This project showed that the concept that machine vision can be applied to cage egg farms. Following further refinement, the technology should provide economic and social benefits for stockpeople and producers. Economic benefits will occur through reduced labour inputs per unit (eg. per cage of birds or per shed) and reduced egg wastage, which should result in savings to the producer and increase profits. Stockpeople will be able focus their time dealing with higher priority work tasks, as they spend less time performing ‘unprofitable’ activities that would be monitored automatically using the machine vision technology. The social benefits for egg producers are probably less tangible but may include the benefits of increased stockperson retention. Stockperson retention may increase due to improved job satisfaction. Governments and the public will have increased confidence that the welfare of hens is better monitored through increased frequency of inspection.</p>

<p><b>Publications</b></p>	<p>Abstract submitted to World's Poultry Congress 2008.</p> <p><b>Efficacy of video image analysis to detect potential blockages on egg collection belts</b></p> <p><b>G.M. Cronin<sup>1*</sup>, S.S. Borg<sup>1</sup> and M.T. Dunn<sup>2</sup></b></p> <p><b><sup>1</sup>Animal Welfare Science Centre, Department of Primary Industries, VICTORIA, AUSTRALIA</b>  <b>greg.cronin@dpi.vic.gov.au</b></p> <p><b><sup>2</sup>National Centre for Engineering in Agriculture, University of Southern Queensland, QUEENSLAND, AUSTRALIA</b></p> <p>Checking mechanical egg belts for blockages is an important task to reduce cracked or broken eggs. In multi-tier cage systems, blockages on egg belts above stockperson eye-level may be more difficult to detect. We investigated whether video image analysis (VIA) could automatically perform this task. VIA is the ability of a computer to 'see'.</p> <p>We placed eggs and other objects at random on egg belts. A camera was transported along the front of the cages, attached to the robot that delivered feed to the feed trough, enabling the egg belt to be recorded on digital video as the robot moved. Trials were conducted at the research institute (70 tests, 6 m belt, total of 2,466 eggs and 293 foreign objects) and a commercial farm (20 tests, 18 m belt, 5,200 eggs and 278 foreign objects). Ninety and 95% of foreign objects, respectively, were detected by the automatic detection algorithm. The incidence of false positives (eggs detected as foreign objects) was 0.1 and 0.5%. The software also reported the detected foreign objects pictorially, assisting the remote recognition of foreign objects and false positives. The results demonstrate that VIA could be used to monitor egg belts for blockage while increasing the time available by stockpeople for less mundane tasks.</p>
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