University of Southern Queensland
Centre for Agricultural Engineering

Novel detection of chicken welfare using machine vision

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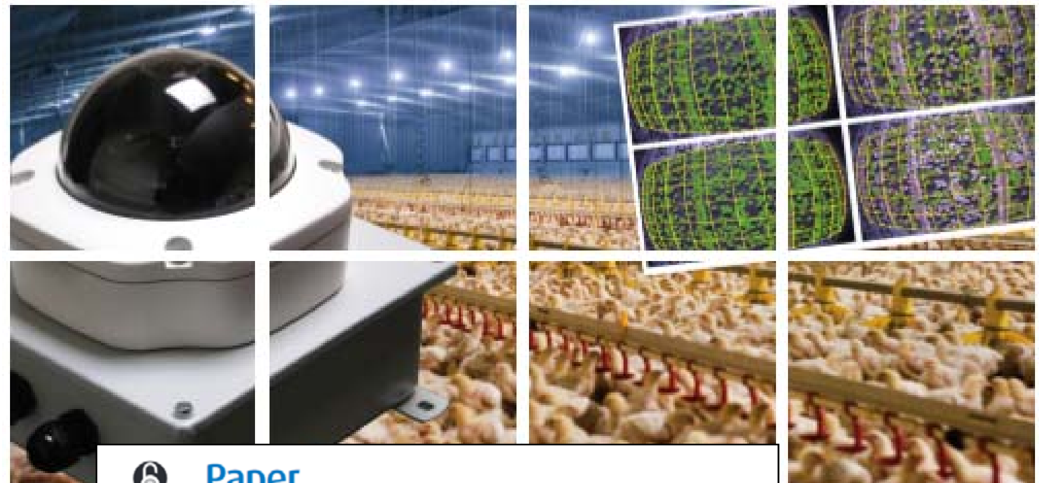
Machine vision for flock monitoring

Many aspects of chicken comfort and condition present visually

- Environmental comfort - hot / cold; behaviours; lesions from wet litter
- Biosecurity threats - visual signs of infectious diseases, e.g. gasping, extension of the neck, pale comb
- Production metrics - weight gain; feed conversion ratio; feeding behaviours

Machine vision monitoring

- Perceives a physical environment through automated analysis of camera images
- Shapes, colours, motion detected via analysis of pixels
- Machine 'sees' as a human, and beyond
- Daily or hourly patterns without disturbance from walking through flock



Source: Fancom

Paper

OPEN ACCESS

Early warning of footpad dermatitis and hockburn in broiler chicken flocks using optical flow, bodyweight and water consumption

M. S. Dawkins, S. J. Roberts, R. J. Cain, T. Nickson, C. A. Donnelly

Footpad dermatitis and hockburn are serious welfare and economic issues for the production of broiler (meat) chickens. The authors here describe the use of an inexpensive camera system that monitors the movements of broiler flocks throughout their lives and suggest that it is possible to predict, even in young birds, the cross-sectional prevalence at slaughter of footpad dermatitis and hockburn before external signs are visible. The skew and kurtosis calculated from the authors' camera-based optical flow system had considerably more power to predict these outcomes in the 50 flocks reported here than water consumption, bodyweight or mortality and therefore have the potential to inform improved flock management through giving farmers early warning of welfare issues. Further trials are underway to establish the generality of the results.

Introduction

Footpad dermatitis (ulcerated lesions of the pad of the foot) and hockburn (discoloration and lesions of the hocks) are serious welfare and economic issues in the production of broiler (meat) can indicate health problems (Butcher and others 1999). However, although the total amount of water consumed over the lifetime of a flock is positively correlated with the prevalence of footpad dermatitis assessed at the slaughter plant (Manning

Source: Dawkins *et al.* 2017

USQ Machine vision for flock monitoring

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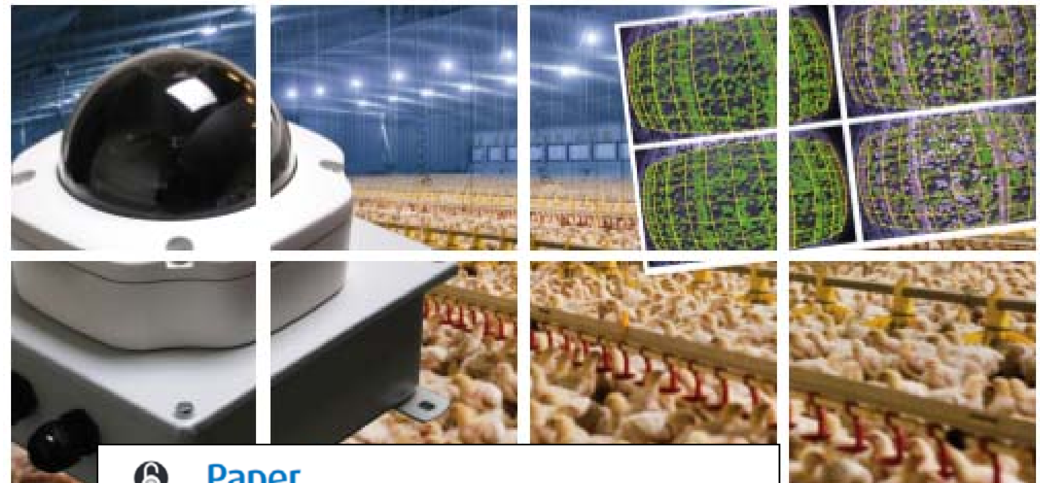
Current state of the art for autonomous monitoring

- Space utilisation
  - Existing commercial system/s
  - Typically installed in ceiling, i.e. top view
  - Birds represented as regions of connected pixels
- Optical flow for flock movement
  - Long-term time series analysis of multiple-flock movement, without inspecting individual birds
  - Camera installed with human viewing perspective
  - Provides early warning of an anomaly
  - A veterinary inspection provides diagnosis of the specific condition
  - Requires image training data of several flocks for each shed
- Various proof-of-concepts for research studies of behaviour



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Machine vision for flock monitoring

Project objectives

- Develop and evaluate image analysis for bird behaviour and welfare monitoring, including optical flow; and develop weight estimation
- Project phases
  - Original project 2017-2019 conducted machine vision evaluations of pen experiments and commercial environments to determine scalability of welfare indicators
  - Project extended into 2019-2021 for further shed evaluations
- Commercial environment focus
  - Such that farmers ultimately have access to the technology as a product
  - Generate automated alerts for detected flock conditions to the grower
- Presentation today will cover practical operational requirements and image analysis results
  - Operational Factor One: Camera physical format
  - Operational Factor Two: Camera viewpoint
  - Operational Factor Three: Camera environment
  - Image analysis results for behaviour monitoring and towards weight estimation

Operational Factor One: Camera physical format

Desirable characteristics of a new technology (for commercial adoption)

- Easy to install (and remove)
- Low setup and calibration requirements
- Low user training requirements
- Low on-going maintenance
- Low-cost and easy to replace
- Multiple uses / multipurpose

Off-the-shelf camera options

- Security cameras
  - Usually lengthy to install and configure, requires infrastructure like network and power
  - Large data bandwidth

- Action cameras
  - Generally high quality images but typically not programmable for automation purposes

- Trail cameras
  - Designed for endurance use with low image quality and low image capture rates

Operational Factor One: Camera physical format

Camera characteristics for a shed environment

- Wireless
    - For data storage and power supply
    - Ease of installation; reduce workplace hazard and risk of damage by rats
- Waterproof and ease of cleaning
    - Washdown between flocks
    - Smooth, non-textured outer surfaces desirable
- Mounting by quick release brackets
    - For ease of removal and repositioning by the user
- Autonomous
    - Put in position and starts operating
    - Minimal software configuration
    - Remote data access
- Desirable if recharge cycle lasts the flock cycle

Camera with long life battery in a waterproof enclosure

- These camera characteristics have enabled camera deployment to remote sites, with camera handling and mounting performed by shed staff
- Records multiple video clips each day

Operational Factor Two: Camera viewpoint

Installation position

- In the ceiling
  - Top view - chickens are represented as a series of 'blobs', suited for space utilisation
  - Can be difficult to discriminate - head and tail; sitting versus standing; feather condition
  - Typically - difficult to install
- On the wall - a human viewing perspective with closer detail

Typical images from literature – top views

Source: Kashiha *et al.* 2013

Source: Naas *et al.* 2012

Scale of attribute to monitor – Bird-level versus flock-level

Algorithm requirements

- In general – continuous & consistent – a regular interval and complete time series is most important
- Need to be robust to slight variations in viewpoint between sheds
- Small amount of training data, i.e. make meaningful discriminations within 1-2 days without prior training

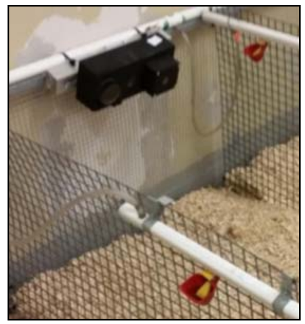
Operational Factor Three: Camera environment

Experimental pens

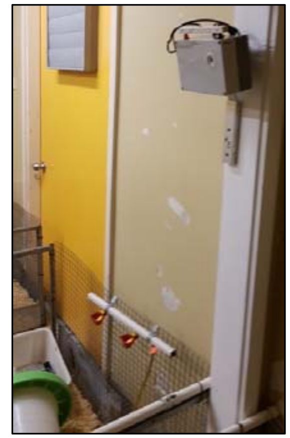
- Useful for evaluating camera physical format and viewpoints
- Birds were more accustomed to humans

Version 1 – wired cameras; top view
Difficult to discern posture and behaviour

Version 2 – wireless cameras; close oblique view
Clearly see body features

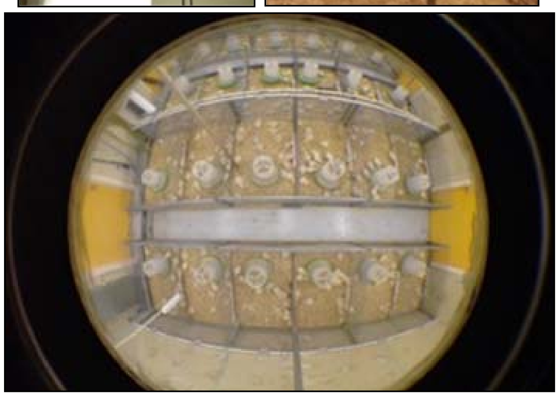


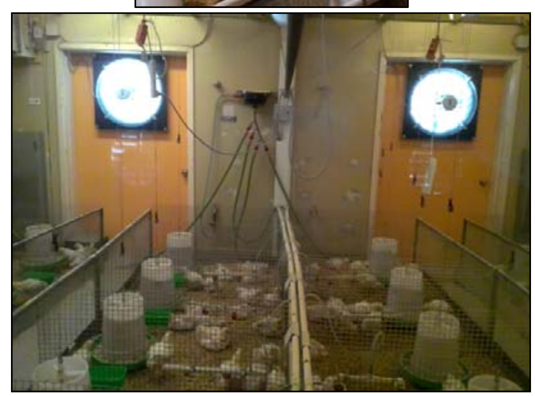
Version 3 – waterproof cameras; mid-range oblique view
Mesh reduces usable image resolution



In a shed

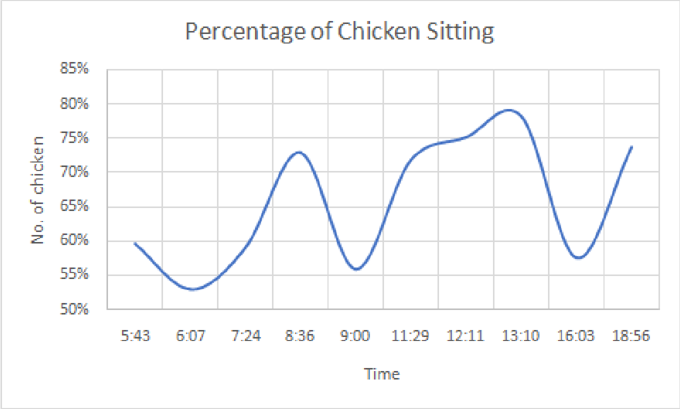
- Free movement of birds on shed floor
- Not as accustomed to humans
- Daily routines were apparent

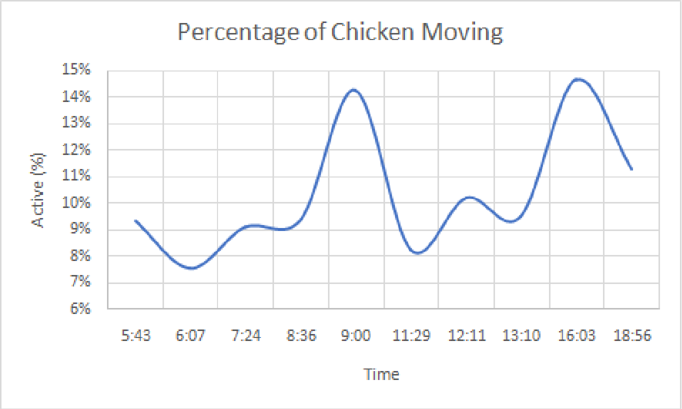


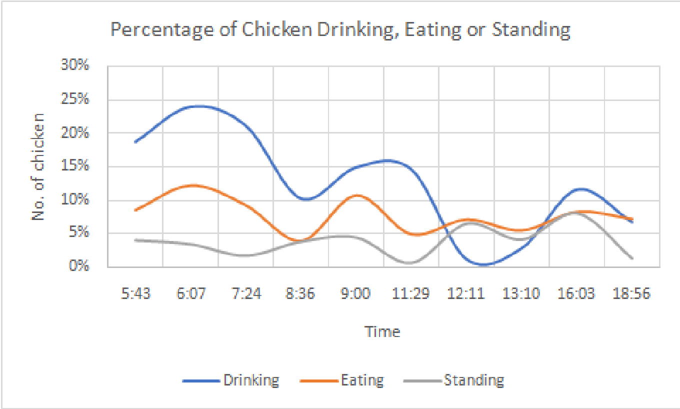


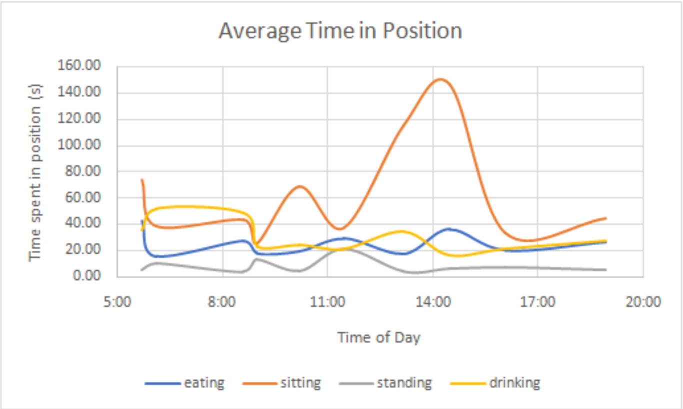
Chicken behaviours: Visual inspection

- Cameras installed in a commercial shed for one flock
- Mid-range oblique view
- Visual inspection consisted of scan sampling, i.e. identifying states of all individuals at predetermined time intervals
- Routine - sitting, eating, drinking, running (only when a person came in)









USQ Chicken behaviours: Image analysis

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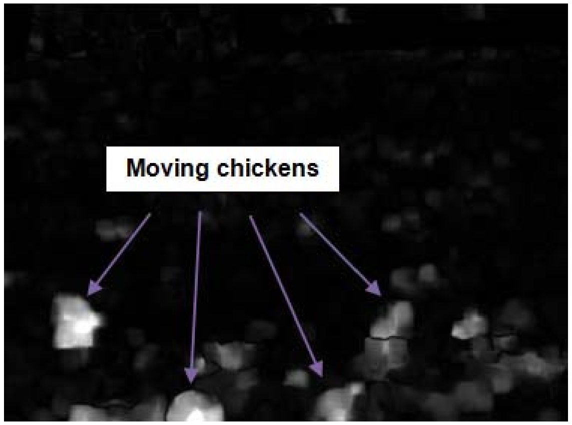
- Optical flow yields flock movement without individual bird inspection
- Additional processing segments individual birds, replicating human inspection for counts of moving birds



Example source of error: 2 chickens sitting close together

Dataset	Date	Manual count of chickens in image	Moving chickens / Total chickens %			Stationary chickens / Total chickens %		
			Manual count	Image analysis	Error	Manual count	Image analysis	Error
Time 1 (e.g. Early morning)	Day 1	68	13.2%	15.6%	**2.4%**	86.8%	84.4%	**-2.4%**
	Day 2	43	9.3%	10.9%	**1.6%**	90.7%	89.1%	**-1.6%**
	Day 3	67	19.4%	22.0%	**2.6%**	80.6%	78.0%	**-2.6%**
						Mean average error		**2.2%**
Time 2 (e.g. Morning)	Day 1	88	3.4%	1.3%	**-2.1%**	96.6%	98.7%	**2.1%**
	Day 2	75	6.7%	6.3%	**-0.4%**	93.3%	93.8%	**0.4%**
	Day 3	103	4.9%	5.0%	**0.1%**	95.1%	95.0%	**-0.1%**
						Mean average error		**0.9%**
Time 3 (e.g. Afternoon)	Day 1	95	6.3%	7.4%	**1.1%**	93.7%	92.6%	**-1.1%**
	Day 2	90	6.7%	2.5%	**-4.2%**	93.3%	97.5%	**4.2%**
	Day 3	94	4.3%	2.6%	**-1.7%**	95.7%	97.4%	**1.7%**
						Mean average error		**2.3%**
Time 4 (e.g. Evening)	Day 1	95	5.3%	1.2%	**-4.0%**	94.7%	98.8%	**4.0%**
	Day 2	110	10.0%	10.2%	**0.2%**	90.0%	89.8%	**-0.2%**
	Day 3	74	8.1%	4.9%	**-3.2%**	91.9%	95.1%	**3.2%**
						Mean average error		**2.5%**

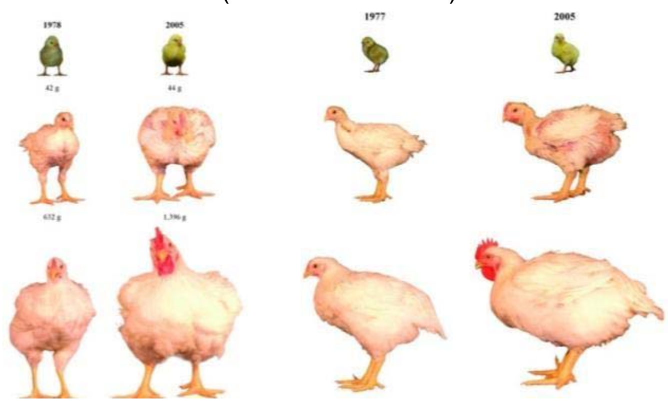
Weight estimation: Literature

Chicken body measurements related to weight

Measurement	Description	Visibility
Body length	Distance along back from base to neck to base of tail	Side view or top view
Chest girth	Circumference of body around the deepest region	Front view
Keel length	Length of body from base of neck to front of legs, i.e. length of sternum	Side view or top view
Pelvis width	Distance across hips	Top view
Body depth	Depth of body at the deepest region	Side view
Shank length	Length of lower leg	Side view or front view
Chest or shoulder width	Distance across body at front of leg, or width across shoulders (where wings join backbone)	Top view or front view

Front and side profiles for different weights

(Zuidhof et al. 2014)



Literature – Animal science

- Multiple body measurements are highly correlated with weight – frequently, prediction models are based on a single body measurement
- Typically, measurements have visibility from side or front views (more so than top views)

Literature – Machine vision

- Cameras are typically installed facing downwards to obtain a top view – such that the chickens are in a fixed object plane (i.e. the floor) to enable linear scaling of distance; and chickens do not occlude each other

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Weight estimation: Machine vision measurements

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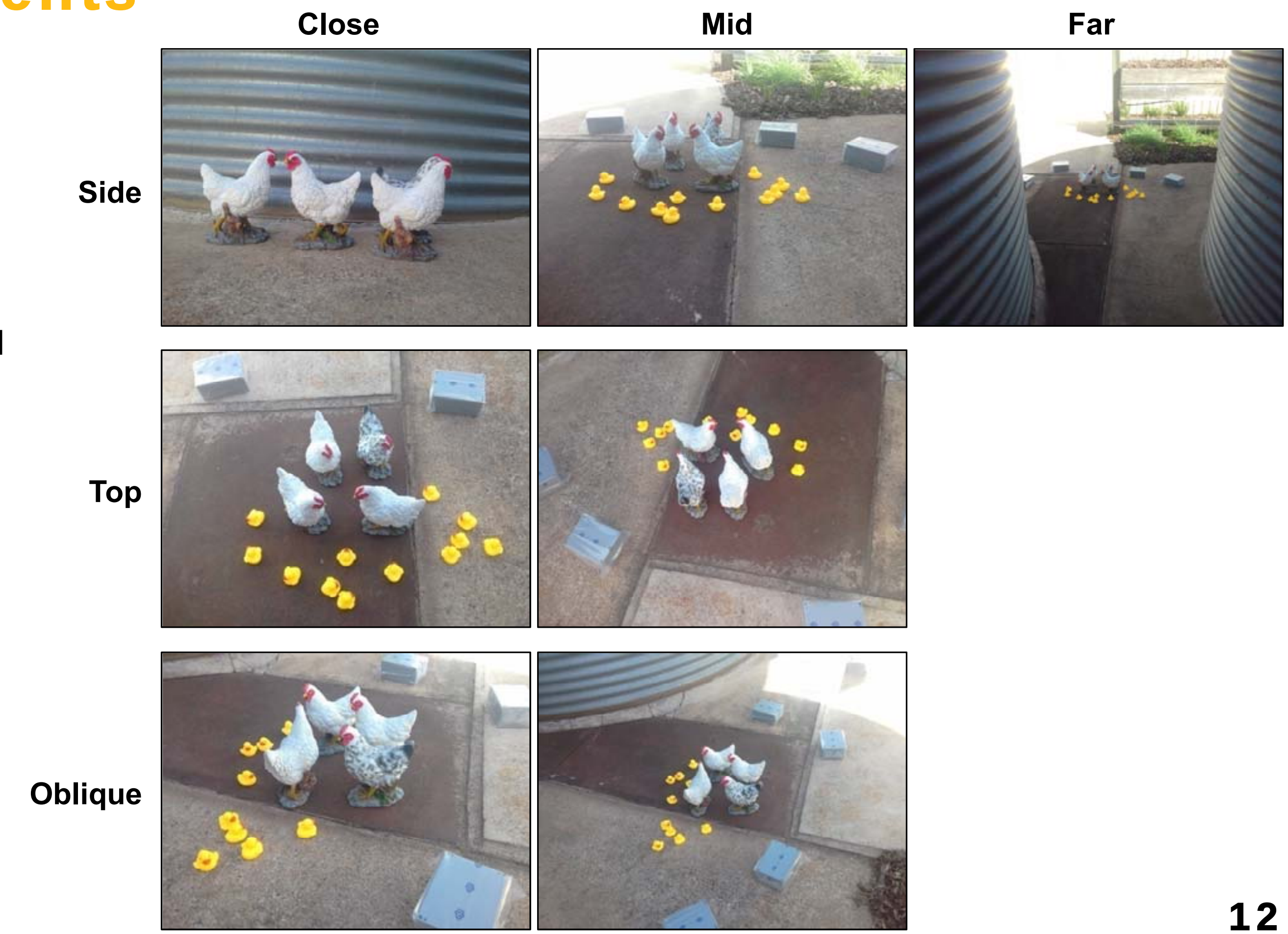
- Machine vision aims:
  - Detect dimensions of birds on an open floor, as opposed to a pen
  - Obtain body measurements for multiple birds simultaneously
- Test views for dimensional accuracy and visibility of body dimensions
- Simulate different camera mounting positions in shed:
  - On the wall
  - In the ceiling
- Replacement of chickens by statues in controlled camera tests
- Other considerations for live birds:
  - Feathers, gender, posture, feeding
  - Larger number of birds on floor



Weight estimation: Machine vision measurements

- Chicken body measurements by supervised selection of points in machine vision data (table below)
  - High accuracy
  - Multiple body measurement instances, simultaneously
  - Automatic scaling between viewpoints
- Automated machine vision workflow for image capture and analysis in a shed – in development

Image set	View/Distance (cm)	Body length from images (cm)	Mean absolute error (mm)	Body length from images - higher resolution (cm)	Mean absolute error (mm)
1	Oblique/70 cm	13.8/13.9/13.5	0.9	13.7/13.9/13.9	0.6
2	Oblique/125 cm	13.4/13.6/13.0	2.2	13.7	-
3	Side/62 cm	14.1/13.0/13.8	1.4	14.0/14.1/13.8	0.3
4	Side/90 cm	14.0	-	13.8	-
5	Side/215 cm	13.5	-	14.0	-
6	Top/75 cm	14.4/13.9	0.6	13.9	-
7	Top/90 cm	13.5/13.5	1.1	14.0/13.8/14.1	0.3

Conclusions and further work

- Machine vision provides additional discrimination ability to what human inspection alone can perform
- Ultimately – minimal calibration requirements; applicability to multiple different flocks at different sites; particular discrimination ability
- Modular cameras potentially lower-cost for small and large farms
- Current work is continuing development of machine vision for sheds
- Technologies are also applicable to outdoor systems

Low-cost solar-powered machine vision of remote outdoor environments from a 5 m tower
Photo Source: Machine vision monitoring of National Variety Trials for Grains Industry

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- Project steering committee
- Participating commercial shed company
- Prof. Robert Swick's team at University of New England for access to experimental pens

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