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MEASURE, MODEL AND MANAGE BIO-RESPONSES USING IMAGE PROCESSING TECHNOLOGY

Mohammad Amin Kashiha

Dissertation presented in partial fulfilment of the requirements for the degree of Doctor in Bioscience Engineering

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Abstract

The welfare of animals in livestock houses is usually monitored manually by the farmers. There was a scientific method developed by ethologists via performing some standardised measures on chosen welfare indicators; however, a large set of measures need increased workload by manual observers or stockmen in order to provide a useful indication of an animal's quality of life. The use of technology will help not only reduce manual workload but also provide continuous monitoring with a more accurate image of livestock health and welfare.

The primary objective of this thesis was to show that image processing technology and mathematical modelling lead to more frequent monitoring of health and welfare related responses of livestock animals. Animal responses were monitored using a single camera per pen with an increasing frequency of data sampling. Manual observations once in a growth period were increased to automatic capturing of one data point per second. The aim was to prove that automated measurements give way to early warning systems and provide greater input into the modern livestock production. Consequently, these methods give a greater insight into the effectiveness of welfare measures.

A general methodology labelled as elliptical (or geometrical) modelling was introduced. The use of this model evolved throughout the thesis. The first step for continuous measuring of livestock variables was to localise them. In Chapter 2, this model was employed to localise pigs in a pen. Pigs were painted with unique patterns to be identifiable for research purposes using automated image analysis. Pigs were tracked in their feeder, drinker, resting and defecating zones.

In the next step, the movement of animals within their living area was examined. This aspect was researched in chapter 3 by using the elliptical model in order to measure pig locomotion. As a result, the pigs' statuses were divided to In-Locomotion and Not-In-Locomotion.

Although variables such as location and locomotion of animals are important, the reason why the animals prefer to appear in certain zones is more meaningful for the farmer. In chapter 4, elliptical modelling was used to investigate if laying hens prefer to attend chambers with lower ammonia levels.

Because the use of the elliptical model could explain why animals choose certain zones in their living area, the effect on their performance became of interest. To understand this, two important indicators of animal's performance were selected: namely weight gain and water volume usage. In chapter 5, the topview body area of pigs were measured using "real-time" image analysis. This area was linked to actual body weight using mathematical modelling. In chapter 6, the number of visits pigs give to their drinker and how long they stay at the drinker was measured by image processing. In this case, real-time mathematical modelling helped link drinking visits and duration to actual water volume used by the pigs. In both cases, mathematical modelling helped interpret livestock variables extracted from the images and linked them to physical variables that indicate the performance of pigs.

In all of the previous chapters, individual animals within a group were studied. However, there are variables (e.g. distribution) that are only meaningful for groups of animals. Additionally, the impact of individual animal performance on groups was examined. In chapter 7, the distribution of broiler chickens was studied. The geometrical model was used to measure how chickens spread around the house and a real-time mathematical model was developed to predict future distribution. Therefore, abnormalities in how group of broilers are distributed could be detected and reported in format of a warning system.

These automatic monitoring techniques developed can be used to complement the manual welfare measures and provide the farmer with relevant management information. Specifically, early warning systems can assist the farmer and the veterinarians to take early action for securing health and welfare of farm animals.

Samenvatting

Het welzijn van dieren in de veehouderij wordt in de praktijk doorgaans manueel gecontroleerd door de boeren. Er werd ook een wetenschappelijke methode ontwikkeld door ethologen via het evalueren van gestandaardiseerde maten voor welzijn op basis van een gekozen set welzijnsindicatoren. Om een volledig beeld te krijgen van de levenskwaliteit van een dier moet echter een groot aantal maten voor welzijn beoordeeld worden, wat een grote werkdruk teweegbrengt voor de waarnemers of de boeren. Het gebruik van technologie zal niet enkel de manuele werkdruk verlagen, maar geeft ook continue monitoring met een accurater beeld van de gezondheid en het welzijn van het vee.

Het doel van deze thesis was om aan te tonen dat beeldverwerkingstechnologie en wiskundig modelleren leiden tot het frequenter monitoren van gezondheid en welzijn gerelateerde dierlijke responsies. Dierlijke responsies werden gemonitord gebruik makend van een enkele camera per hok met een toenemende samplefrequentie. Eenmalige manuele observaties per groeiperiode werden verhoogd tot het automatisch vastleggen van één meetpunt per seconde. Het objectief was om te bewijzen dat geautomatiseerde metingen een vroegtijdige waarschuwingen systeem mogelijk maken en een grotere bijdrage leveren tot de moderne veehouderij . Bijgevolg geven deze methoden een groter inzicht in de effectiviteit van maten voor dierenwelzijn.

Een algemene methodologie gelabeld als elliptisch (of geometrisch) modelleren werd geïntroduceerd. Het gebruik van dit model evolueerde gedurende de thesis. De eerste stap voor het continue meten van diervariabelen bestond uit het lokaliseren van het vee. In Hoofdstuk 2 werd dit model toegepast voor het lokaliseren van varkens in hun hok. Varkens werden gemerkt met unieke rug merktekens om voor onderzoeksdoeleinden identificeerbaar te zijn door middel van automatische beeldverwerking. Vervolgens werden de varkens gevolgd in hun voeder-, drink- en ontlastingszones.

In de volgende stap werd de beweging van dieren in hun leefomgeving bestudeerd. Dit aspect werd onderzocht in Hoofdstuk 3 door gebruik te maken van het elliptische model om de beweging van de varkens te meten. Vervolgens werd voor de status van de varkens onderscheid gemaakt tussen In-Beweging en Niet-In-Beweging.

Hoewel variabelen zoals positie en beweging van dieren belangrijk zijn, is de reden waarom dieren liever in bepaalde zones verblijven betekenisvoller voor de boer. In Hoofdstuk 4 werd het elliptisch model gebruikt om te onderzoeken of legkippen een voorkeur tonen voor het verblijven in kamers met een lagere ammoniakconcentratie.

Aangezien het gebruik van het elliptisch model kon verklaren waarom dieren bepaalde zones in hun leefruimte verkiezen, ontstond de belangstelling voor het effect hiervan op hun prestatie. Om dit te begrijpen, werden twee belangrijke indicatoren voor dierprestatie geselecteerd, namelijk gewichtstoename en waterconsumptie. In Hoofdstuk 5 werd de lichaamsoppervlakte vanuit bovenaanzicht gemeten met behulp van "real-time" beeldverwerking. Deze oppervlakte werd gekoppeld aan het werkelijke lichaamsgewicht doormiddel van wiskundige modellen. In Hoofdstuk 6 werd het aantal bezoeken van varkens aan de drinkbak en de tijdsduur van ieder bezoek gemeten met behulp van beeldverwerking. In dit geval hielp een real-time wiskundig model om het aantal bezoeken en hun tijdsduur te koppelen aan de werkelijke waterconsumptie van de varkens. In beide gevallen hielp wiskundig modelleren bij het interpreteren van diervariabelen die berekend werden uit de beelden en bij het vinden van een verband tussen deze diervariabelen en de fysische variabelen die een indicator zijn voor de prestatie van varkens.

In alle voorafgaande hoofdstukken werden individuele dieren binnen een groep bestudeerd. Er bestaan echter variabelen die slechts betekenisvol zijn wanneer ze op groepsniveau bekeken worden, zoals ruimtelijke verdeling van de dieren. Daarnaast werd de impact van de individuele dierprestatie op groepen onderzocht. In Hoofdstuk 7 werd de verdeling van vleeskippen bestudeerd. Het geometrische model werd gebruikt om te meten hoe kippen zich over de stal verdelen. Een real-time wiskundig model werd ontwikkeld om toekomstige ruimtelijke verdeling te voorspellen. Bijgevolg konden abnormaliteiten in de ruimtelijke verdeling van vleeskippen gedetecteerd worden en gerapporteerd worden in de vorm van een waarschuwingssysteem.

Deze ontwikkelde automatische monitoring technieken kunnen gebruikt worden om de manuele maten voor dierenwelzijn aan te vullen en de boer te voorzien van relevante managementinformatie. In het bijzonder kunnen vroegtijdige waarschuwingen systemen de boer en de veeartsen helpen om vroeg actie te ondernemen om gezondheid en welzijn van dieren te waarborgen.

List of Abbreviations

2D	Two Dimensional
3D	Three Dimensional
AFO	Animal Feeding Operations
AU	Animal Units
AWES (lab)	Animal Welfare and Environmental Systems (Laboratory)
BW	Body Weight
CCD	Charge Coupled Device
Comp	Compartment
CPU	Central Processing Unit
CSV	Comma Separated Values
DC	Direct Current
dd	Day in format [0-3][0-9]
DPPAs	Densely Populated Poultry Production Areas
EPC	Environmental animal Preference Chamber
EU	European Union
eYe	eYeNamic system
FAO	Food and Agriculture Organisation
FD	Fourier Description
FE	Feeding

FMD	Foot-and-Mouth Disease
FN	False Negative
FP	False Positive
fps	Frame Per Second
GHz	Giga Hertz
HPAI	Highly Pathogenic Avian Influenza
Hz	Hertz
ICT	Information and Communication Technologies
ID	Identity
IL	In Locomotion
ImLS	Image Locomotion Status
IP	Internet Protocol
IPS	Image Processing System
IR	Infra-Red
IT	Information Technology
kbps	kilo bits per second
kg	kilo gram(s)
LL	Lying Laterally
LS	Lying Sternally
m	Meter
M3-BIORES	Measure, Model and Manage Biological Responses
MATLAB	Matrix Laboratory
min	minute(s)
mm	Month in format [0-1][0-9]
MPEG	Moving Pictures Experts Group
MTT	Minimum Transitional Tunnel
NE	North East
NH3	Tri-hydrogen nitride (Ammonia)
NIL	Not In Locomotion
NW	North West

OCC	Occupancy
OIE	Office International des Epizooties (World Organisation for Animal Health)
PC	Personal Computer
PhD	Doctor of Philosophy
PLF	Precision Livestock Farming
ppmv	Part Per Million by Volume
RAM	Random Access Memory
RFID	Radio Frequency Identification
RGB	Red-Green-Blue
RO	Rooting
TF	Transfer Function
TVL	TeleVision Line
SD	Standard Deviation
SE	South East
SISO	Single Input Single Output
SW	South West
TP	True Positive
VIA	Visual Image Analysis
Vol	Volume
WA	Walking
YIC	Young Identification Criterion
yyyy	Year in format [00-99][00-99]
ZOD	Zone Occupancy Density

List of Symbols

Δd	Change of distribution index
Δt	Change of time
θ	Ellipse (body) orientation
θ_T	Difference of orientation between ellipses
θ_V	Angle of view
°C	Celsius (degree)
$\measuredangle$	Angle operator
alpha (α)	Statistical significance level
α	Threshold coefficient
A	Topview body area
a	Predicted slope of the current light period
a_i	i^{th} coefficient in nominator polynomial
$a_i(z^{-1})$	Nominator polynomial
b	Final distribution index value in the previous light period
b_i	i^{th} coefficient in denominator polynomial
$b_i(z^{-1})$	Denominator polynomial
BW(t)	Body weight at time t
C	Number of cameras
C_i	Centroid of ellipse i

d(t)	Half-hourly duration of visits to drink nipple
d(p,q)	Euclidean distance between query patterns p and q
E_i	Ellipse *i*
Ev_i	Event time label
f(i,j)	Image function for pixel (i,j)
h	Hour
t	Ceiling Height
h_c	Camera Height
i	Point i on contour of an image
$I_a(x, y, t)$	Locomotion image pixel value of point (x,y) at time t
ImL	Image Locomotion
ImL^Y	Image Locomotion of pigs for yesterday
ImLS	Image Locomotion Status
$ImLS^T$	Image Locomotion Status Threshold for today
k	kilo (1000)
kg	kilogram(s)
l	Length
L	Average size of major axis of ellipses
p	FD coefficients of pattern P
q	FD coefficients of pattern Q
mp	Distance between base of head side triangle from the centre of the paint pattern painted on a pig
m^2	Squared meters
M	Number of rows of zones
m_{pq}	(p^{th} ,q^{th}) order torque of image function
n	Number of coefficients in calculating Fourier Description
N	Number of columns of zones
n_a	Order of nominator polynomial
n_b	Order of denominator polynomial
np	Body length of a pig

n_T	Number of time delays between each input i and their first effects on the output
O(x,y,t)	Occupancy of zone (x,y) at time t
R^2	R-squared (Coefficient of determination)
t	Time; in seconds
$\overrightarrow{T}$	Movement vector (from ellipse E_1 to ellipse E_2); in pixels
T	Size of the movement vector; in pixels
td	Discrete-time increments for weight estimation and measurement
$U_{i,j}(t)$	Binary value of zone occupancy
UI(t)	Distribution index at time t
w	Width
w(t)	Half-hourly water volume usage
X	Input of a function (model)
$X_{centroid}$	Width coordinate of centroid of an image
Y	Output of a function (model)
$Y_{centroid}$	Length coordinate of centroid of an image
$ZOD_{i,j}(t)$	Zone Occupancy Density of zone (i,j) at time t
$\overline{ZOD(t)}$	Average occupancy rate of all zones in an image

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Chapter 1 Introduction

“Engineers like to solve problems. If there are no problems handily available, they will create their own problems!”

Scott Adams

1.1 Modern livestock production

Livestock is one of the fastest-growing sectors in agriculture, potentially presenting opportunities for economic growth, poverty reduction and changing diets in rural areas. Dealing with the important social, environmental and public health issues linked to, sector growth will require solutions that embrace the way in which the livestock sector grows to meet increasing demand for animal-source foods. It is important therefore to understand where growth in demand for livestock commodities is likely to occur, and how and where production of livestock commodities will be increased in order to meet it (Otte et al., 2007).

As countries have become more affluent, the demand for livestock-derived food has substantially increased, leading to a major transformation of global animal food production. The linkage between sub-sectors of the animal industry, such as feed manufacturers, breeding companies, livestock keepers and processors, as well as production practices have changed significantly over the past decades, with potentially serious consequences for disease risks. These changes include significant increases in livestock populations and densities, using fewer but more productive livestock breeds and lines, with, in the case of poultry and pigs, hybrid animals providing the end product, specialisation in and vertical integration of stages of production (e.g. breeding, raising, finishing), and major changes in the design of animal housing facilities.

Intensive animal production involves high throughput animal husbandry in which thousands of animals of similar genotypes are raised for one purpose (such as pigs, layer hens, broiler chickens, ducks, turkeys) with rapid population turnover at one site under highly controlled conditions, often in confined housing, with nutrient dense, industrial feeds replacing access to forage crops. In the US, these facilities are known as Animal Feeding Operations (AFOs). Concentrated Animal Feeding Operations (CAFOs) are a type of AFO, which have a regulatory definition in the US as facilities that have animals stabled or confined for at least 45 days out of any 12 month period and holding at least 1000 Animal Units (AUs) (1 AU = 1000 pounds body weight = 45.36 kg body weight).

Globally, pig and poultry production are the fastest growing and industrializing livestock subsectors with annual production growth rates of 2.6 and 3.7 per cent over the past decade (table 1-1). As a consequence, in the developed countries, the vast majority of chickens and turkeys are now produced in houses in which between 15000 and 50000 birds are confined throughout their lifespan. Increasingly, pigs and cattle are also raised under similar conditions of confinement and high density. The trend towards industrialisation of livestock production can also be observed in developing countries, where traditional systems are being replaced by intensive units at a rate of 4.3 per cent of animal holding units per year, with much of that increase occurring in Asia, South America and North Africa (Otte et al., 2007). In developing countries a large proportion of industrial units are sited in or close to human population centres. Over the same time, the human population has grown by almost 700 million people, again, with much of this growth occurring in the developing world and in particular affecting urban populations.

Table 1-1. Changes in global human population, pig and poultry inventories, and production and international trade of pig and poultry meat between 2006 and 2014. Source: FAOSTAT website (faostat.fao.org)

	2006	2014	Annual growth (%)
Human population	5 762	6 451	1.1
Inventory			
Pigs (million)	859	963	1.1
Poultry (million)	14 949	18 428	2.1
Production			
Pig meat (thousand tons)	79 375	103 226	2.6
Poultry meant (thousand tons)	56 408	81 856	3.7
International trade			
Pig meat (thousand tons)	6 398	9 557	4.0
Poultry meant (thousand tons)	5 359	9 234	5.3

Industrialisation of food animal production has led to major increases in livestock productivity, which is, to a large extent, the result of genetic progress and the development of diets tailored to specific stages of production. For poultry and pigs, industrial production is organised in stages that separate primary breeders, multipliers and producers which are a small number of globally operating companies forming the apex of the breeding pyramid. Different production stages are often undertaken at different sites, leading to significant movement of live animals, at times across national borders. In 2005, for example, more than 25 million live pigs, i.e. more than 2 million pigs per month, were traded internationally (Prakash and Stigler, 2012). In the US, there is a huge movement of unfinished animals, for example feeder pigs[1] from the Carolinas to the Cornbelt. In 2001, 27 per cent of pigs in the US were moved from one state to another (or more) (Hennessy et al., 2004). Investigations in relation to the recent HPAI[2] outbreak in the UK revealed that links in poultry production within one enterprise between facilities located in the UK and in Hungary involved movement of hatching eggs, birds and poultry products four times before the final product reached retail (Lucas, 2007). Animal slaughter operations have also become concentrated, leading to larger average distances for transport to slaughter (Burrell, 2002).

Consequences of intensive farming in Europe are also obvious. Industrial broiler chickens are bred to reach a weight of 2.2 kilograms in just five weeks (Lymbery, 2012). This is well beyond their natural limits and causes great suffering. A typical stocking density in the UK and Europe for broiler chickens is equivalent to around 17–20 birds per square metre as they approach slaughter weight, i.e. a space allowance of less than one A4 sheet of paper per chicken. Every year, an area of forest equivalent to half the UK is cleared, much of it to grow animal feed and for cattle ranching. An area of land equivalent to the size of the European Union is used to grow feed for farm animals globally. Piglets born into factory farms often have their tails docked and their teeth clipped, usually without any form of anaesthesia. There are over 260 million cows used to produce milk in the world, including

[1] Feeder pig is a weaned gilt or barrow weighing between 18 kg and 37 kg at 6 to 8 weeks of age that is sold to be finished for slaughter (Pitcher and Springer, 1997)

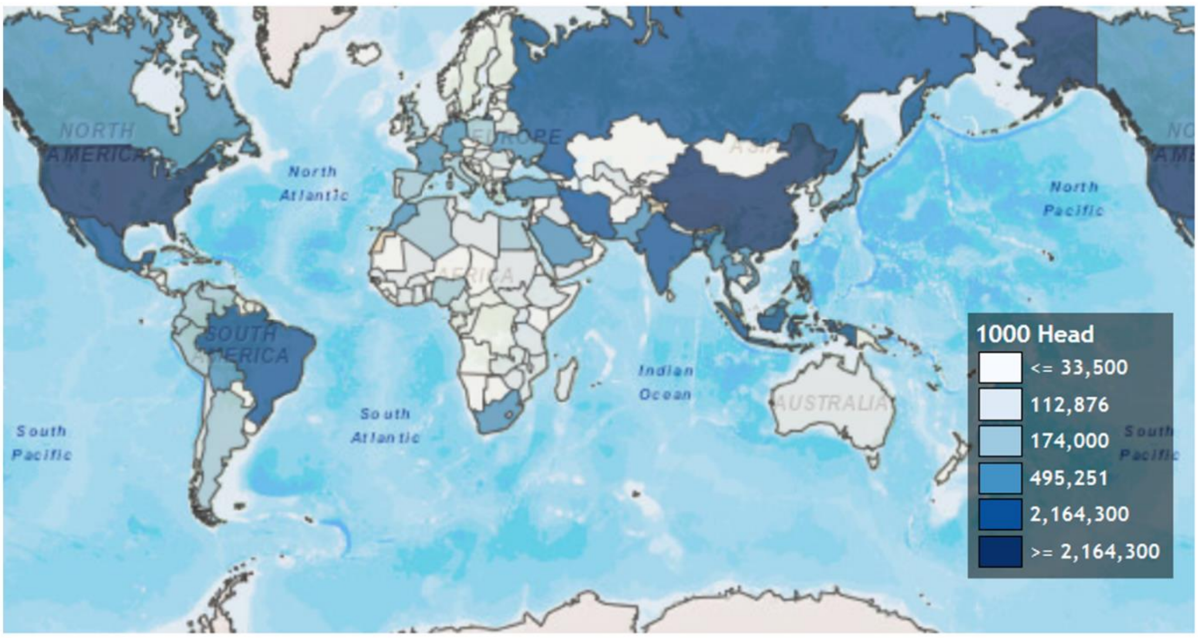
[2] Highly Pathogenic Avian Influenza

24 million in the European Union (EU). A kilogram of beef takes the equivalent of 90 bathtubs of water to produce. More than 326 million rabbits are farmed for food in the EU every year, with the majority being kept in cramped barren battery cages. For the production of “foie gras”[1], force-feeding geese increases the size of the liver by up to ten times and the fat content of the liver exceeds 50% (Lymbery, 2012).

The consolidation of poultry and pig production for reasons of competitive advantage has also affected the geography of food animal populations. Over the past 60 years, the geographic distribution of both pig and poultry production in the US, for example, has become more clustered, with poultry production now being highly concentrated in the south eastern states and pig production concentrated in some of these same states, as well as in the Midwest. Similar trends have occurred worldwide with pig and poultry populations increasingly concentrated in particular locations that are often geographically coincident. An approximate overview of the global distribution of poultry and cattle population densities is provided by figure 1-1 a and b.

Geographical concentration of pig and poultry production has seen an associated increase in global trade and movement of pig and poultry meat products, which over the past decade has increased at an annual rate of 4.0 and 5.3 per cent, respectively (table 1-1). Although trade can be considered safe when conducted in line with OIE[2] regulations, poultry trade has been implicated in the cross-border spread of H5N1 in Asia and Africa (Kilpatrick et al., 2006).

Number of poultry heads by country (2013)

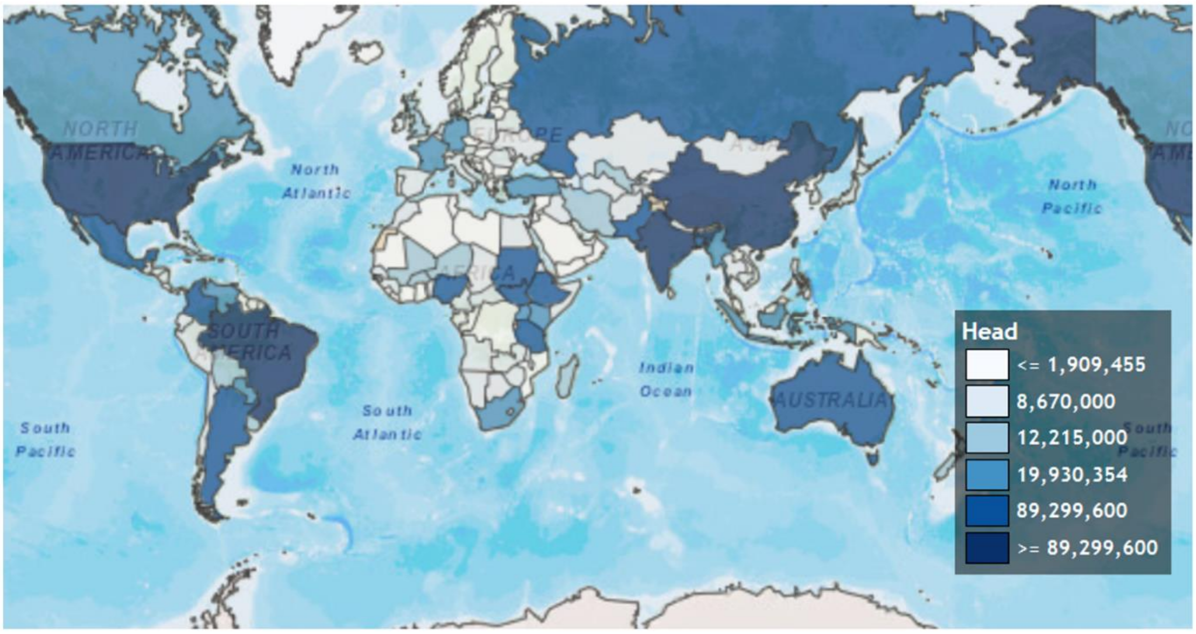


(a)

[1] French for “fat liver”

[2] OIE stands for “Office International des Epizooties” which is translated as “World Organisation for Animal Health”

Number of cattle heads by country (2013)



(b)

Figure 1-1. Global poultry (a) and cattle (b) distributions (Courtesy of FAOSTAT: faostat.fao.org)

It can be more profitable to raise or move animals for 'finishing' to locations where animal feed is abundant, e.g. close to feed mills, than to continuously move feed over large distances. Therefore, areas of high livestock density have emerged in a number of regions worldwide. Semi-vertical integration of production processes, where a large company supplies young stock and feed, while farmers provide animal housing and labour, has often not been accompanied by systematic spatial planning of the units in the system. Although spatial concentration is convenient from an organisational point of view, as illustrated in the case of the HPAI outbreaks in DPPAs[1], it has serious drawbacks for the control of epidemic diseases. In the EU, location specific disease risks, as for example determined by concentration of production units or proximity to wildlife reservoirs, are not factored into the cost of production because the current tax-financed system of disease outbreak response acts as a free insurance of last resort, and thereby results in the generation of avoidable amounts of 'risky' production (Jansson et al., 2006). The same authors show that although moving to risk-based compulsory insurance for FMD[2], financed by the livestock sector, would not result in major relocation of dairy production within the EU, it would lead to a fairer distribution of disease control costs between member countries and between consumers and producers. The location of poultry and pig production, which does not rely on the availability of grazing land, may shift in response to a risk-based insurance system.

[1] Densely Populated Poultry Production Areas
[2] Foot-and-Mouth Disease

Considering all above consequences that follow from intensive livestock farming, continuous monitoring of livestock health and welfare throughout the fattening process is crucial. Technology could facilitate this using frequent measurement of livestock variables[1].

1.2 Principles of Precision Livestock Farming

The use of modern information technology (IT) can play a crucial role in the early detection of disease and assessment of welfare in modern livestock production. IT systems can supplement the skills of the farmers, veterinarians and inspectors. With the help of this technology, farmers and veterinarians can continuously and automatically collect and manage the information needed to make sure livestock production is safe, humane and environmentally sustainable (Banhazi et al., 2012).

Sensing systems might facilitate monitoring of many variables in livestock production such as feeding times, feed intake, animal health and behaviour. Monitoring is carried out preferably in real-time, based on analysis of animal measurements such as sounds, images, live weight and condition score. The overall goal is to achieve a continuous assessment of the state of livestock and their environment in terms of health, welfare, performance and environmental related issues. Mathematical models are used for animal data evaluation in many livestock processes.

Precision Livestock Farming (PLF), which is based on the above concepts, is the management of livestock by continuous automated real-time monitoring and/or controlling of production or reproduction, health and welfare of livestock (Berckmans, 2012). Processes suitable for the PLF approach include animal growth, aspects of animal behaviour and the physical environment of a livestock building, such as its thermal micro-environment and emissions of gaseous pollutants such as ammonia (Wathes et al., 2008).

PLF consists of measuring variables on the animals, modelling these data to select information, and then using these models in real time for monitoring and controlling purposes. The PLF information provides an essential component of Farm Assurance Schemes throughout the food chain, helping to minimise risks to the consumer and guarantee product quality (Berckmans, 2009). This technology can be used for surveillance and monitoring at the level of the individual animals, pen, farm, region, or country. Thereby, PLF is currently regarded as the heart of the engineering endeavour towards sustainability in livestock related food production. Its application allows making optimal use of knowledge and information in the monitoring and control of processes with livestock (Berckmans, 2008).

The main purpose of PLF is to improve the efficiency of production, while increasing animal and human welfare, via applying advanced Information and Communication Technologies (ICT), targeted resource use and precise control of the production process. In this section, a brief review of the current scientific state of art and, more importantly, the

[1] Livestock variable is defined as an element which quantifies a status, behaviour or physical characteristic of an animal farm (Blokhuis et al., 2010)

implementation of PLF technologies with the view to facilitate more effective technology transfer between scientific and commercial organisations is given.

1.2.1 The role of PLF

Through the adoption of electronic data collection, processing and application, precision farming has the potential to improve production efficiency and reduce costs, as well as increase animal and human welfare. There is currently an abundance of information available to livestock managers, but it is not generally structured in a way that can be applied readily. For example, a survey of producers raising beef from pastures in southern Australia showed that over 400 types of information could be relevant for their farms. The information comes from many sources including academic organisations, government advisors, producer magazines, media sources, technical advisers and other producers. Consequently, farm managers tend to adopt procedures in areas where they have most interest or in which they believe they have most expertise and neglect many other areas that are also essential to drive productivity and profitability. Furthermore, many producers perceive that adopting high productive management systems involves increased risk. The perceived risks include financial failure because of unforeseen environment or market circumstances, damage to the farm infrastructure such as soils and pasture, compromises to animal health and welfare, and increased stress on farmers from managing an intensified system. These risks are real. Thus, it is important to develop a management system that ensures that the essential procedures are carried out, that they are all carried out correctly and consistently, and in a way that controls risk (Banhazi et al., 2012).

The fact that humans tend to lose consistency with the application of repetitive tasks is one of the main reasons for failure of manually handled systems. Recording and checks of measurements and actions by other people is one way to help overcome the problem. The difficulty faced by many rural industries in industrialised countries is obtaining and retaining adequately trained and motivated staff. The lack of good staff frequently contributes to the failure of well-planned adoption programs[1].

The major role for PLF is to simplify this process of collecting, processing and analysing data so that the farm manager is presented with solutions to his/ her problems. Advances in the application of the outlined procedure for adoption of essential enterprise processes will depend more and more on the automated measurement, interpretation and control of these processes. The procedure should include automation of all measurement systems, interpretation of the measurements, identifying when critical measurement limits are breached and built-in automatic control systems for each essential process to bring it back inside the acceptable limits. A useful example of the type of change needed within the animal industries comes from the international steel industry. In the 1950s, all tasks were undertaken by humans compared with today when the whole process is controlled electronically, almost all manual work tasks are automated and monitored centrally. Workers are trained to work with machines instead of doing hazardous and heavy manual work themselves. This is a vision for PLF, where animal welfare, environmental

[1] "Adoption programs" are programs designed to transfer between an old system to a better and more modern system

sustainability, productivity and profitability are all at an optimum using electronic measurement, interpretation and control systems.

1.2.2 Technological developments and applications

Many of the early PLF developments were predominantly instigated in EU/UK. Early pioneers of the PLF concept were researchers at Leuven University, Belgium, the Silsoe Research Institute, UK and University of Wageningen, The Netherlands. Additional developments took place in other EU countries, such as Germany, Denmark, Finland and the Volcani Research Centre, Israel (Devir et al., 1997).

Recent developments in communication technology offer a huge potential benefit to the performance, design, application and value of PLF. In order to make use of these benefits the centralisation of data collection and management can play an important role. Whilst independent applications on individual farms may be desirable to some customers, the advantages of centralised data collection, processing, management and reporting are significant. For example, data collected by sensors on the farm can be sent to a central site for processing, storage and reporting. This could result in considerable time saving for farm managers to be allocated for more productive tasks, such as farm and animal husbandry related tasks. The centralised processing should supply him with only the data pertinent to his daily needs, with more detailed reports available as required, including through the centralised database the comparative performance of his unit, for example. In short, the benefits offered by a good PLF system should be obvious to the user and ideally should reduce his management workload (Lehr, 2011).

In livestock production there are already a few examples of practical implementation of PLF techniques. Good examples of adoption of PLF techniques include the use of robotics in dairying, measurement of water usage, egg counting, bird weighing, better control of environment in poultry houses, computerised feed systems, climate control, automated disease detection, growth measurement and real-time production site data capture in piggeries (Guarino et al., 2008). The EU sponsored BrightAnimal project (Lehr, 2011) has looked for evidence of PLF technologies in laying hens, pigs, dairy and aquaculture used in a commercial environment in a number of countries, including Estonia, Denmark, Norway, United Kingdom, Australia, Malaysia, Vietnam and South Africa. In general, however, there was limited evidence of commercial PLF products used on farms. This was because, although PLF sensor systems were widely used to collect data, management systems which go one step further and "interpret" the data were rarely adopted on farms. As expected, farmers in techno-friendly countries like Estonia, are more inclined to use technology to reduce their dependency on hard-to-get and expensive workers and make their life more comfortable. However, even in there, the amount of deployed technology is very limited and key aspects of animal welfare or productivity are not monitored in an automated fashion routinely.

The commercialisation principles of PLF technologies need to include (1) a verification of the benefits of the PLF technique being proposed, (2) a clear communication of those verified benefits to customers, (3) identification of principle beneficiaries (i.e. operator vs. owner of the business), (4) provision of appropriate training and technical support, (5) correct specification, installation, commissioning and monitoring of the installed system.

In order to increase the interest of suitable companies in providing services to farmers, collaboration between smaller specialist firms and larger generalist firms is desirable. Transferring PLF technologies to companies supplying and managing the systems is a significant step towards developing commercial PLF tools and products that are wanted by customers and sold with confidence.

1.3 Image processing technology in PLF technique

Animals require individual care, attention, and measurement. With the growing number of livestock mentioned in section 1.1, this cannot be done by famers themselves because number of animals per caretaker is highly increased compared with only 10-15 years ago (Lundborg, 2004). Therefore, technology can assist them in managing their farm animals.

Fortunately, new technology is now reaching the point where its application to biological processes has become realistic. Wireless data transmission, for example, is becoming cheap and reliable. The sensor and sensing technologies (e.g. camera, microphone) that are needed to develop products have become small and reliable enough to be used within the harsh environment of livestock production. Unit costs are also decreasing. For example, the worldwide success of devices such as mobile phones has reduced the cost of wireless communication and is pushing this technology into other applications such as monitoring livestock health and welfare technologies. Moreover, the livestock market involves huge numbers of animals and processes, making it possible to produce customised, applied technology at reduced costs. One might wonder why the producers of smart phones have not started by providing wearable technology for over 60 billion animals that are slaughtered every year for food production. An automated system is cheaper than the cost of experts such as veterinarians and feed consultants visiting farms: a fully automated system, 24 hours (h) a day, seven days a week, costs the same as just four farm visits by experts (Berckmans, 2014).

Automatic monitoring of animals based on real-time image analysis is an approach, which has been applied in various animal species (DeShazer et al., 1988; Tillett et al., 1997). It can also be useful to farm managers (Burke et al., 2004; Aydin et al., 2010; Venter and Hanekom, 2010).

Farm managers gain a great deal of information from the appearance of an animal. The purpose of real-time image processing technology is to enable some of the available information to be extracted automatically by connecting a camera to a processing platform equipped with the appropriate hardware and software. Computer algorithms segment the objects of interest and interpret the visual scene. This is particularly difficult for biological objects. The visual characteristics of biological objects exhibit a variability that is not generally present in manufactured objects. The mobility and deformability of animals contribute extra visual variability. Further difficulties are due to the rather uncontrolled conditions in which animals are kept, meaning that it is difficult to arrange for the animal to be presented to the camera under favourable lighting conditions and against a background which makes segmentation easy (Frost et al., 1997).

Substantial progress has been made researching these generic problem areas. For instance, an approach for locating an object is to match a model of it with candidate objects in the image. For manufactured items it is usually straightforward to construct the model, since the dimensions are known. However, animals have variable dimensions and can adopt various poses. The model must therefore be deformable. This approach has been demonstrated (Tillett, 1991) by an algorithm in which a model of a pig can be rotated, translated, scaled and bent laterally to find a good match within an image containing a pig.

Algorithms have also been developed to enable the outline of an animal to be constructed from an image in which the animal has an indistinct or incomplete boundary. A particularly useful technique is based on the snake algorithm, in which the mechanics of an elastic loop stretched around the image of the animal are simulated. Consideration of the energies involved has enabled a boundary to be located in situations where conventional techniques have failed (Marchant et al., 1999).

An extension of image analysis research, which has relevance for monitoring animal behaviour, is the segmentation and tracking of moving objects. Tracking animals is nontrivial as they are difficult to identify and their movements are often unpredictable. One approach is to use image differencing with respect to a time-averaged background. In this technique the current image is compared with a reference image, based on previous images. This enables areas of change within the image to be differentiated from an invariant background. The areas of change are candidate animals, which can then be confirmed or rejected by model-based algorithms (McFarlane and Schofield, 1995). Tillett et al. (1997) have extended the idea of using a trainable flexible model for locating pigs in images to tracking animal movements through sequences of images. The technique was used to model subtle motions such as bending and head nodding, as well as position and rotation. This approach could be used to characterise animal behaviour over time.

Some of the current applications with potential of being implemented in animal production in future in particular include feather sexing poultry chicks, in which accuracies of up to 89% have so far been achieved (Tao and Walker, 2002), evaluating meat quality (Tan, 2004), determining carcass quality of live pigs (Doeschl-Wilson et al., 2004), determining live fish size (Zion et al., 2007) in which the lengths of swimming fish have been measured and monitoring cattle behaviour (Cangar et al., 2008).

Potential applications usually include extraction of information relating to the shapes of animals which could be used, for example, in conformation assessment in pigs and cattle, and body condition scoring in dairy cattle. Repeatable quantitative measurements of animal conformation would be valuable on the farm for monitoring production, and will be increasingly valuable in association with electronic marketing of stock. Analysis of the movement of individual animals could give early warning of abnormal conditions such as lameness (Poursaberi et al., 2010).

Most of above applications rely on 2D images. But progress has also been made in the extraction of three-dimensional information from the livestock. This could be implemented through the extraction of three dimensional information from two dimensional images or by using 3D cameras such as Kinect (Van Hertem et al., 2014). In the former, deductions relating to the structure or conformation of the object can be made. One approach has been through the use of stereo imaging. Two cameras are used to produce pairs of images of the object. The cameras are arranged so that points on the object can be identified and located in both images. From a knowledge of the geometrical arrangement of the cameras and the locations of the corresponding points in the pairs of images the three dimensional coordinates of the points can be calculated. An alternative approach involves the analysis of the deformation caused to structured lighting when it is projected onto a three dimensional object.

Nowadays, stereo imaging systems have been mostly replaced by direct 3D image acquisition cameras such as Kinect which has recently gained popularity. Kinect is a composite device consisting of a near-infrared laser pattern projector, an Infra-Red (IR) camera and a colour (RGB[1]) camera. The IR camera and projector are used as a stereo pair to triangulate points in 3D space. The RGB camera can be then used to texture the 3D points or to recognise the image content. As a measuring device Kinect delivers three outputs: IR image, RGB image, and a depth image. The latter has appeared to be a very useful Visual Image Analysis (VIA) variable in monitoring performance and behaviour of livestock (Viazzi et al., 2014).

Using VIA, farm managers not only can monitor their animal's performance and behaviour in real-time, but they will also be able to predict these behaviours and potentially avoid welfare problems using image-based early warning systems. To achieve this goal, boundary conditions in livestock production could be monitored using camera technology in order to optimise desired outputs and minimise undesired outputs.

Figure 1-2 illustrates the livestock production as a process with inputs used to produce relevant outputs (bio-responses). Improving animal health and welfare (boundary conditions) using VIA technology could improve desired outputs, i.e. product quality, quantity and safety. This can be achieved by ensuring good health and welfare. Health and welfare are closely linked to animal behaviour and performance that could be measured by VIA.

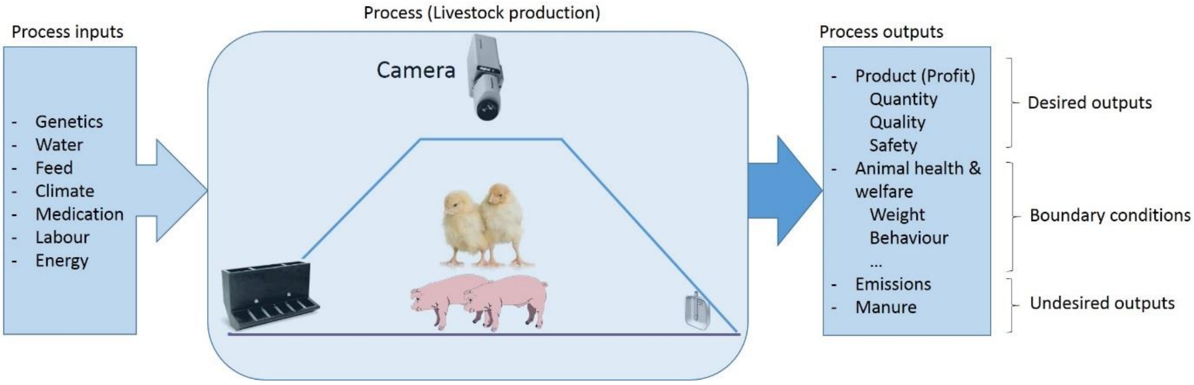


Figure 1-2. Livestock production process with inputs and outputs

A straightforward example of behaviours that could be measured using VIA is drinking behaviour and water volume usage. Water is a fundamental need for pigs and inadequate access to it may result in reduced feed intake, reduced production and increased health problems (Gonyou, 1996). Monitoring of the drinking behaviour of young pigs, has proved

[1] Red-Green-Blue: The RGB colour model is an additive colour model in which red, green, and blue light are added together to reproduce a broad array of colours.

to be a useful tool in detection of diseases and other production related problems too. For instance, it is known that by on-line monitoring of drinking behaviour of young pigs, an outbreak of diarrhoea can be detected approximately one day before physical signs are seen on the pigs (Madsen and Kristensen, 2005b). Thus, a camera as a non-contact sensor could be used for disease prediction through monitoring drinking behaviour. In conclusion, it is beneficial to develop an automated monitor for drinking behaviour of pigs in a pen.

Monitoring animal's performance could also be an indication of welfare and health status. An important performance indicator is individual weight gain. However, individual weight measurements suffer from a number of drawbacks when performed manually. Gathering performance data using a manual scale is therefore done sparingly, generally only at the beginning and end of a production period and most often only for a representative subset of animals, and not for every animal (Schofield, 1990). Machine vision-based weighing of pigs is a non-intrusive, fast and accurate approach, which could reduce stress for both the animal and the farmer during the weighing process (Wang et al., 2008). Since slow weight gain can happen for some of the pigs in a pen, it is important to monitor weight for each pig individually. This helps the farmer to make appropriate management changes.

Although many image processing techniques have been developed for measuring livestock variables, no solid integration of these measurements has been reported in literature. Moreover, interpretation of behaviours measured is missing from results of the previous works. For instance, one technique might be able to measure abnormal locomotion in pigs, but it fails to understand why some pigs are less locomotive in a group. In another example, it is known that distribution is a meaningful group behaviour in livestock, but no research work has reported interpretation of abnormalities in this variable. These are the two challenging problems we try to solve in this PhD in order to fill the gap in state of the art in PLF. Firstly, we are going to investigate if many functions could be integrated in one single sensor, namely a camera. Secondly, we would like to understand what new horizons interpretation of animal behaviour using real-time image processing technology could open up for farm managers. What is new in this PhD is the link established between the variables measured by real-time image processing and helpful information that could actually be used by farm managers to improve health and welfare of their animals.

1.4 Hypotheses and objectives

Observing animal-based variables is essential to ensure livestock are in good health and welfare. For more than four decades, human observations of such variables have been taken as basis for welfare and health assessment of animals on farm and at slaughter (Dawkins, 1980). As a systematic approach a European research project. i.e. Welfare Quality, was realised to develop a method for scoring animal welfare in field situations. In this project a definition of principles and criteria of good welfare was suggested. Standard animal-based measures were developed for each welfare criterion. The Welfare Quality® project focussed on integration of animal welfare in the food quality chain: from public concern to improved welfare and transparent quality. The project aimed to accommodate societal concerns and market demands, to develop reliable on-farm manual scores, product information systems, and practical species-specific strategies to improve animal welfare. Animal welfare measures[1] were integrated in an overall assessment model for three main species: cattle, pigs, and poultry. It was proposed to send experts to livestock farms throughout Europe to assess the measures on the farms. This should be either done at the end of a fattening period or once a year (Blokhuis et al., 2010).

A main problem with the current scoring technique (based on Welfare Quality protocols) lies in the time and cost needed for a complete assessment on the farm. Hygiene, workload and corresponding costs limit frequent visits to farms. There are a lot of animal-based measures (e.g. body condition score) involved but they are not frequently measured throughout the life of the animal. This is why these measures are usually only measured at the end of the growth period.

There are several livestock variables per welfare measure that need to be quantified[2]. Although these livestock variables could be quite complex, economical limitations do not allow using a wide range of sensors for so many barns existing in a commercial farm. The **first hypothesis** of this thesis is that many different functions of the system are implementable using **one single sensor**, namely a single camera above a pen of pigs or an area of broilers. Since all the functions have to be fulfilled using one camera, it is required that all used algorithms can run fast without using too much calculation power.

Automated measurements of welfare measures can help to have a better understanding of animal's health and welfare status thanks to the possibility of making high frequency measurements of livestock variables. There are many livestock variables that can be measured automatically. This ranges from physical variables[3] to behaviours. The **second hypothesis** of this thesis is that livestock physical variables (e.g. water volume usage) are linked to behaviour (e.g. drinking). Thus, having knowledge of one could help understand the others better. Image processing allows automated measuring of physical variables through monitoring relevant behaviours and modelling the mentioned link.

Although livestock physical variables and some behaviours are mainly measured on an individual level, there are behaviours such as distribution that are only meaningful at group (pen) level. The **third hypothesis** is that measuring and monitoring both **individuals and group** of animals is of importance but emphasising on either of these depends on the objective of the analysis. As an example, while tracking individuals is important for assessing behavioural responses of animals, group behaviour such as distribution of animals can be meaningful too.

All above techniques are meant to fill the gap in continuous welfare monitoring of livestock through measuring livestock variables. The **first objective** of this thesis is to analyse how physical and behavioural variables could be measured in real time using Image

[1] Welfare measures are measures taken on an animal unit that are used to assess a welfare criterion. A welfare criterion represents a specific area of welfare concern that has to be addressed to satisfy good animal welfare. An example of a welfare criterion is "absence of prolonged thirst" which can be linked to "water supply" measure (Blokhuis, 2009).

[2] For instance, in pigs, back fat is measured for quantifying "body condition score" (Maes et al., 2004)

[3] A variable is physical variable if and only if its value uniquely expresses and characterises some physical situation, hence some physical phenomenon, of matter (including any material object and any being) and/or of energy (Michel et al., 2003).

Processing as a technique of PLF. Changes in behaviours, development of abnormal behaviours or other physiological indicators of welfare can only be captured by using the appropriate frequency of measurements. By continuous monitoring with the appropriate frequent sampling of specific livestock variables (or bio-responses) and calculating welfare/health indicators, one can qualify and improve the animal welfare during the lifetime of the animal. Manual assessment of welfare indicators can report an accurate status of the animals, but it is a momentaneous observation and very expensive. Therefore automatic high frequent monitoring techniques are needed. The **second objective** of the thesis is using image analysis to demonstrate a technique that can assist the farmer and stocks personnel to manage their animals in a more efficient way via frequent measurement of livestock variables.

1.5 Framework of the thesis

This thesis is composed of six articles, all published in peer reviewed scientific journals. Each study is presented as one chapter. Two different animal species were studied, namely pigs and chickens (broilers and laying hens). Consequent chapters deal with applying a generic geometrical model for measuring different behaviours and physical variables in the species mentioned above. The idea is to prove that one general model could define behaviour and/or physical variable of livestock. Image processing technology will be employed together with mathematical modelling to quantify variables in livestock environments. This is carried out in real-time at frequency of one sample per second. Evolution of the chapters is as follows.

1.5.1 Localising where the animals are

Localising animals in an image is the first step towards measuring any variable on the animal and interpreting the measurements. It allows tracking them and identifying their location at any moment. Having state of the art knowledge of animal behaviour allows linking information resulting from localisation to behavioural activities. This context is explained in **chapter 2** by using fattening pigs as an example specie. Localisation could help understand how animals move in their living area.

1.5.2 Understanding how animals move within zones of their living area

The activity level of individual animals is a key factor to their performance and well-being (Beker Yousuf, 2006). Abnormality in animal activity is observed as deviation from its normal locomotion (either an increase or decrease) (Anil et al., 2002). This deviation can be detected and reported to the farmer using automated tools. In **chapter 3**, the focus lies on tracking pigs and their locomotion. Monitoring animal locomotion in groups is an essential aspect of analysing different behaviours. For instance, locomotion is known to be linked to agonistic behaviour, freezing behaviour, ease of movement and thermal comfort. Now that it is known how animals move, the reason why they move or avoid to move to certain areas should be explored.

1.5.3 Understanding why animals move

Although animal locomotion and occupancy of a certain zone is already interesting for assessing its welfare, the reason why the animal attends the zone is more relevant for interpreting the animal behaviour. Investigating how animal behaviour can be interpreted, choice and preference tests, in combination with automated monitoring techniques, can be applied. For instance, it is important to understand how ammonia concentration could affect laying hens since this could have a negative effect on egg production (laying hen's performance). In **chapter 4**, we aim to make an algorithm for monitoring laying hens in an environmental preference chamber. Being able to automatically monitor and interpret how and why animals move, is the basis for understanding how this affects the performance. Important indicators of animal performance are weight gain, drinking behaviour and feeding behaviour.

1.5.4 Discovering how movement of animals and appearance in certain zones affects the performance

Example 1: weight gain

Weight gain is one of the most important indicators of animal performance in the fattening process. Thus, individual weight measurement is an important variable in farm management. However, utilizing manual scales for this purpose is labour intensive and requires movement of animals, which can be stressful for both the animals and workers. In **chapter 5**, we try to develop fully automated weight estimation of pigs. This helps the farmer to check slow-growing animals and to make appropriate management changes to ensure animals deliver a satisfactory performance.

Example 2: Water volume usage

Another indicator of fine performance is drinking behaviour and water intake. Inadequate access to water may result in reduced feed intake, reduced production and increased health problems (Gonyou, 1996). **Chapter 6** discusses development of an automated monitor tool for water volume usage by pigs in a pen. The findings of the study reported in (Musial et al., 1999) indicate that water intake for the pig follows a drinking pattern. This pattern is affected by different factors such as drinker design (Brumm et al., 2000), diet (Shaw et al., 2006), weight and size of pigs (Frederick et al., 2006), etc. Thus, analysing this pattern can yield useful information on suitability of pig's welfare.

Most animals are kept in groups and in particular production systems (poultry) it is still difficult to monitor performance, health and welfare on individual level. Therefore, it is worthwhile to investigate if we can make a link between group behaviour and animal health, welfare and performance.

1.5.5 Understanding how movement of animals affects the group

In **chapter 7**, we test the fully automated identification of problems, such as feeder and drinker malfunctioning in a broiler house by measuring distribution index for a group of broilers. These problems could affect performance of the group and better be detected and reported to the farmer so that he can take appropriate early action.

1.5.6 Discussion and conclusion

In the discussion section, the results of all chapters are evaluated and the potential of applying Precision Livestock Techniques in more frequent monitoring of health and welfare related responses of livestock is discussed.

Finally conclusions are drawn from the entire work and a summary of the contributions of the thesis is made.

Chapter 2 Automatic Identification of Marked Pigs in a Pen Using Image Pattern Recognition

***Article title**: Automatic Identification of Marked Pigs in a Pen Using Image Pattern Recognition*

***Authors**: M. Kashiha, C. Bahr, S. Ott, C. Moons, T. Niewold, F. Ödberg, D. Berckmans*

***Source**: Computers and Electronics in Agriculture, Vol. 93, pp. 111-120*

2.1 Introduction

At present, over 60 billion animals are slaughtered yearly for food production (Prakash and Stigler, 2012). The increasing demand for animal products fosters intensive animal husbandry. Market demands force producers to increase the number of animals in their flock or herd with fewer available resources (per animal). To meet the demands of the market while providing enough care to the individual animals, farmers might use automatic tools to monitor welfare and health of their animals (Harris et al., 2001; Botreau et al., 2007; Morris et al., 2012). While existing systems facilitate an efficient use of land and labour, the increased number of animals per farm has resulted in new welfare problems because time is too limited to provide individual animal care (HSUS, 2010).

One of the essential components of welfare in animal husbandry is providing adequate food and water (Bierer et al., 1965) which requires a substantial number of man-hours. In normal situations pigs show a stable diurnal drinking pattern (Madsen et al., 2005). Abnormal decrease or increase of food or water volume usage can be due to health problems or other factors such as environmental changes or interruptions in feed delivery (Madsen and Kristensen, 2005). A sudden, 20%-30% drop in water volume usage or drinking visits often indicates that swine influenza has taken hold (Bernick, 2007). It is possible to give early alarm in case of such happenings, using image processing techniques. Since all living organisms are individually different, the feed and water volume usage should be monitored per individual pig. Moreover, since individual pigs are anticipating to face these health or welfare problems, it is important that feeding and drinking are detected for each pig individually. This could, in turn, help to prevent the disease from spreading to other pens. Since video analysis of pigs has numerous other applications (Van der Stuyft et al., 1991; Xin, 1999; Kollis et al., 2007) continuous analysing pigs' behaviours using videos can generate added value.

Other researchers previously investigated different approaches to monitor livestock using image analysis. Chedad et al. (2000) employed image analysis to quantify the behaviour of pregnant ewes in field conditions. They developed an algorithm to distinguish laying and standing behaviour in ewes. Using only these two behaviours, they could quantify change of behaviour in 66% of pregnant ewes 6 to 7 h before birth. Based on these results they concluded that online behaviour monitoring of pregnant animals in order to detect the beginning of parturition might be possible. There were other studies investigating the same topic on other livestock. Cangar et al. (2008) used geometric image variables to classify specific behaviours such as standing, lying, eating or drinking of cows. They could categorise 85% of the standing and lying and 87% of the eating or drinking behaviour of the eight cows 24 h before calving using those variables. Image analysis techniques could also be used for smaller and laboratory animals such as rodents. Farah et al. (2011) proposed a method to track rats and determine their motion pattern in cages under normal laboratory conditions. They employed a sliding window approach based on gradient and intensity features consisting of a fitness cost function based on the histograms of oriented gradients, the histograms of intensity, the quantity of motion and edge density to track the animal. They succeeded in achieving adequate tracking with an average error less than 5%. Ahrendt et al. (2011) developed a pig tracking system algorithm based on support maps. These support map segments were subsequently used to build up a 5D-Gaussian model of the individual pigs, their position and shape. Using this method, they could track a minimum of three pigs for at least 8 minutes (min). Aydin et al. (2010) applied an automatic image monitoring system to assess the activity of broiler chickens with different gait scores (ability to walk). Poursaberi et al. (2009) developed an algorithm based on image analysis to classify the behaviour of turkeys in real time and automatically. They chose four behaviours, namely turning, lying, standing and wing flapping to represent different behaviours for welfare assessment. Finally, they fitted ellipses to turkey's body parts and made a model to categorise above behaviours.

In this chapter, an approach is tested to identify pigs in experimental conditions and for behaviour-related research in a fully automated way based on continuous image analysis. To the authors' knowledge there currently is no tool available that uses vision technology to automatically identify marked pigs in a pen. Other researchers previously investigated techniques such as pig identification using ear-tags (Burose et al., 2010; Prola et al., 2010) but there are biosecurity risks raised by this method (Hernandez-Jover et al., 2008) and pigs endure extreme pain in the installation process (Leslie et al., 2010). Vision-based pig identification technology, however, is a non-intrusive technique which has never been analysed so far.

2.2 Materials and Methods

2.2.1 Animals and housing

Experiment of this work was carried out in Agrivet research farm, Merelbeke, Belgium. Forty pigs, RattlerowSeghers x Piétrain Plus, were selected after the battery period and assigned to four fully slatted pens *(2.25 m x 3.60 m)* made of concrete, so there were 10 pigs per pen. Each pen was equipped with a double feeder space and one drink nipple. Animals had ad libitum access to food (commercial grower diet) and water for the whole experimental period. Pigs had a timer controlled 12 h light period from 07.00 h – 19.00 h. Barn temperature was kept on average at 22°C, with a minimum of 18.6°C and a maximum 25.4°C over the total experimental period by Hotraco IRIS climate control equipment. On average, piglets had a weight of 27 ± 4.4 kg at the start of experiments and 40 ± 6.5 kg at the end.

The feeding regime (daily amount of food per pen) was based on ad libitum access to feed (commercial grower diet). Each pen was equipped with a Honsberg Magnetic-Inductive MID008 water meter. These water meters had an accuracy of 2.5% of measured value at the range of 2 to 10 litre/min and an accuracy of 0.5% of full scale at the range of 0.05 to 0.2 litre/min. There was a nipple in the end of each pipe that had to reduce the flow to prevent the pigs spoiling water. Water meters were recording the measured water flow measurement each 5 min.

This study was approved by the Ethical Committee of the Faculty of Veterinary Medicine at Ghent University, Belgium. The experiments carried out in this work were also in accordance with EU Directive 2010/63/EU for animal experiments.

2.2.2 Equipment and data collection

During the experiment, video recordings of the pigs in four pens were made. Cameras were installed in the rafters of the barn at height of 180 cm in the location shown in figure 2-1 to capture topview images. Since 1991 topview camera has been known as a non-disturbing method for monitoring animals and provides a way to implement algorithms in research and field applications (Van der Stuyft et al., 1991). Exact position of the camera in relation to barn dimensions is shown in figure 2-2.

Using MPEG Recorder software from Noldus and black and white Panasonic WV-BP330 camera with CS-mount DC[1]-Servo ALC 5.5-12 mm lens, images were recorded in light intensity of a minimum of 11.7 lux and a maximum of 176.1 lux during 13 days for 12 h per day, between 07.00 and 19.00, resulting in 156 h of video. Videos were recorded in MPEG-1 format, with a frame rate of 25 frames per second (fps), frame width of 720 pixels, frame height of 576 pixels and data rate of 64 kbps. Black and white cameras were used since they were already installed in the barn. To provide light in the barn, six 58 watt, 120 cm Gamma white fluorescent tube lamps were installed at a height of 200 cm in locations shown in figure 2-1.

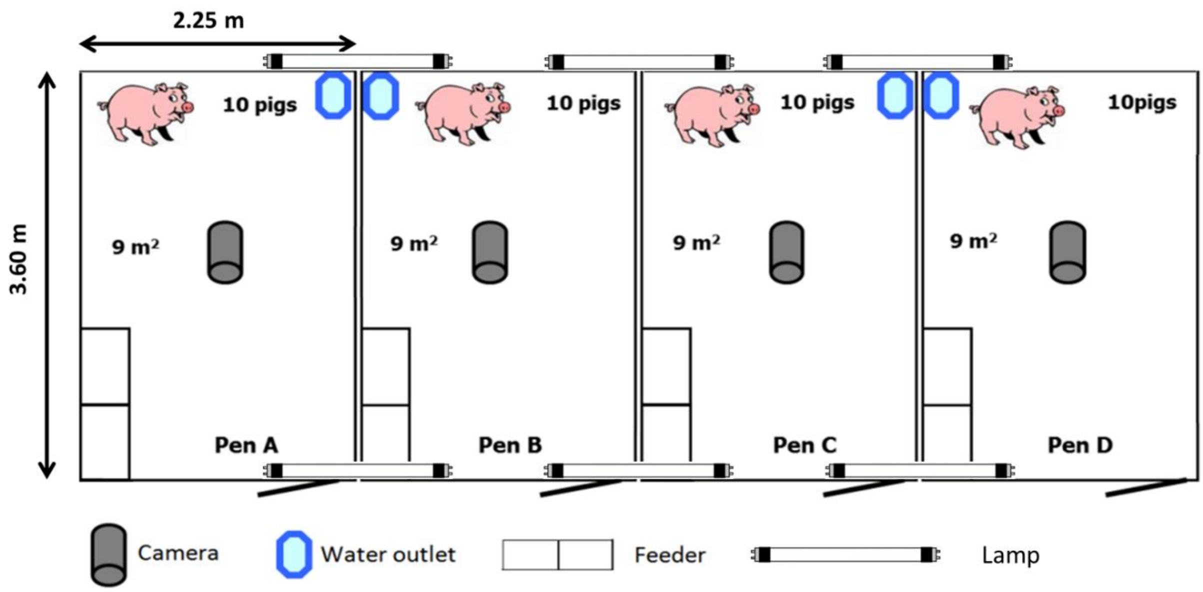


Figure 2-1. Ground plan of the 4 pens in research barn in Agrivet, Merelbeke.

[1] Direct Current

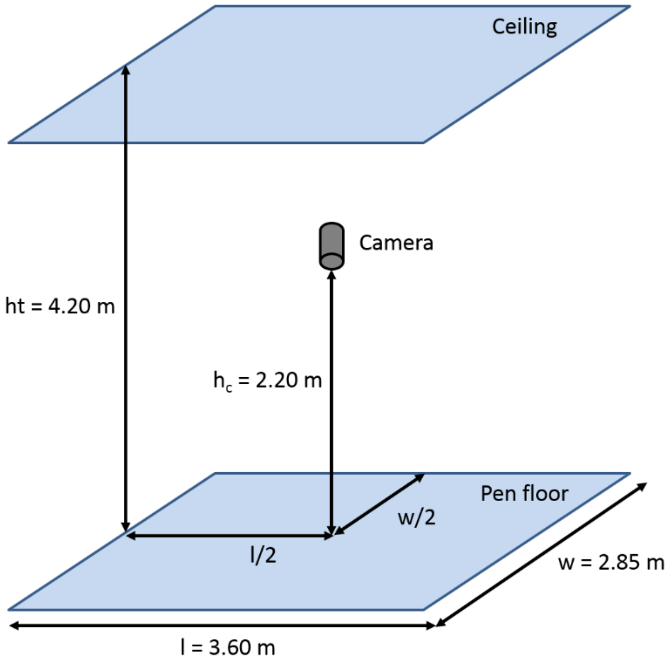


Figure 2-2. Position of the camera on top of a pen

To be able to identify pigs individually, a specific pattern was stamped on the back of each pig using blue dye mark of blue MS Long spray, Belgian MS Schippers. These patterns were cut on rubber in size of 8*12 cm and stamped on pigs' back. On average, the patterns had to be renewed every third day. The reasons this method was used were: 1) it was cheap; 2) it was easy to be implemented; 3) it was computationally feasible; 4) black and white cameras were already available in the barn. Figure 2-3 shows the identification patterns used to identify 10 individual pigs and figure 2-4 shows a frame of a video recorded in the experiment. The patterns selected were required to be discernible using the identification method explained in section 2.2.3.

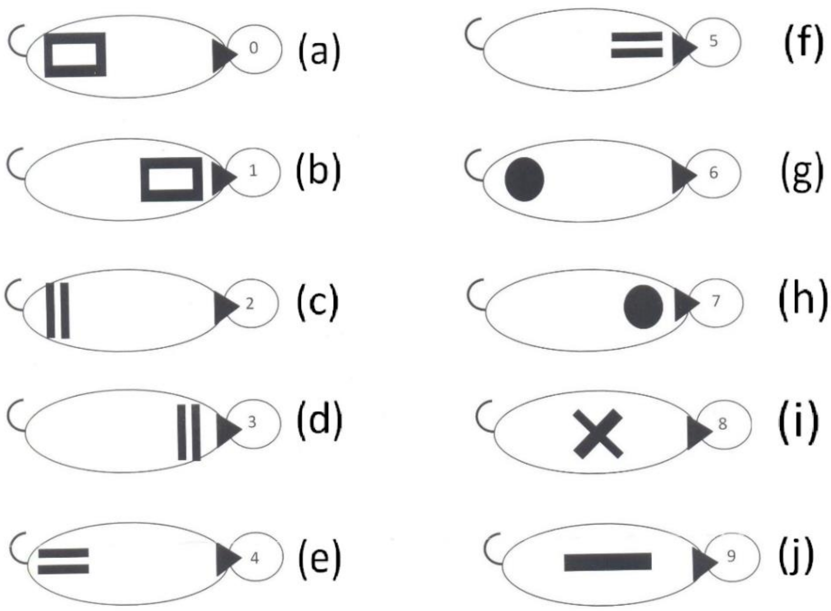


Figure 2-3. Patterns applied to identify 10 pigs in a pen

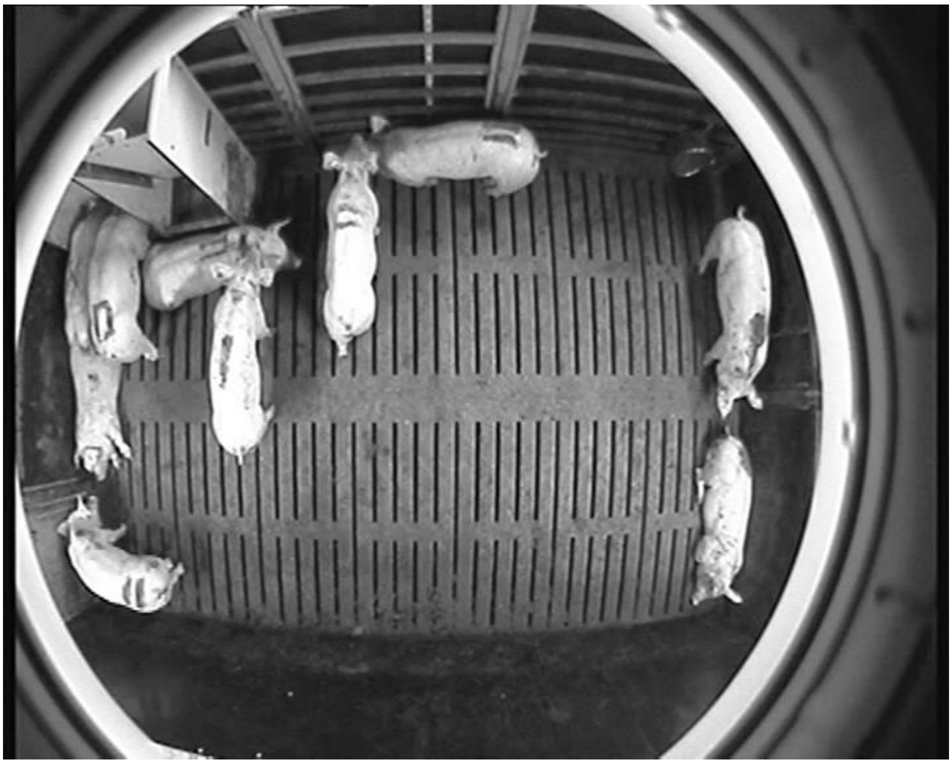


Figure 2-4. A frame of a video in the database

To develop algorithms for continuous automated identification of pigs the identity (ID) and location of each pig are needed to be known during a certain period. As a reference or gold standard of IDs, manual or visual "labelling" of recorded videos was done by an experienced ethologist. Subsequently, a comparison was made between data obtained by manual labelling and data from automatic identification. Manual labelling is a very time consuming work and since labelling of one hour of video takes at least three hours, 468 h were needed to label videos of our experiments (156 h of videos). Since it was not possible to label all the data collected, video samples of 10 min every 2 h were labelled, so that time-of-day effects would have been eliminated. Location of each pig was pinpointed in scan samplings of 2 min (one single frame each 2 min). Therefore 30 samples per pig per day were analysed. The rest of data that were not labelled manually were analysed by localising and tracking pigs. Results of these analyses are presented in section 2.3.

2.2.3 Automated identification of pigs

There are several ways to analyse these patterns (Zhang and Lu, 2004). In this work a method to identify patterns, namely Fourier description (FD) of patterns (Zhang, 2002)(Zhang and Lu, 2004; Zhang and Wu, 2011) was employed. This method is capable of describing objects in an image under very noisy image conditions with numerous variations in the pattern sought (Reddy and Chatterji, 1996; Zhang and Lu, 2004).

The processing flowchart to identify marked pigs in a pen is shown in figure 2-5. The first step to process these patterns was to segment the image in order to find the location of the pigs and the location of the applied identification pattern. To segment the image, first the feeder and the pen floor area were determined. The former was needed to be excluded since it could affect the segmentation accuracy. The latter was necessary to exclude the camera cover appearing in the image from segmentation. These regions are shown in figure 2-6. Thereafter to eliminate light effects, histogram of the image was equalised using adaptive histogram equalisation (Sherrier and Johnson, 1987). Original and histogram equalised images are shown in figure 2-7a and b together with related histograms. Afterwards, the image was binarised to eliminate the background. The binarisation procedure was as follows. First, the image was filtered using a 2D Gaussian low-pass filter. Then, a global threshold was calculated using Otsu's method (Otsu, 1979). The image was hard-thresholded subsequently resulting in figure 2-8a. To remove small objects from the image, a morphological closing operator using a disk-shaped structuring element with size of 10 pixels (Gonzalez and Woods, 2001) was performed on it, resulting in figure 2-8b.

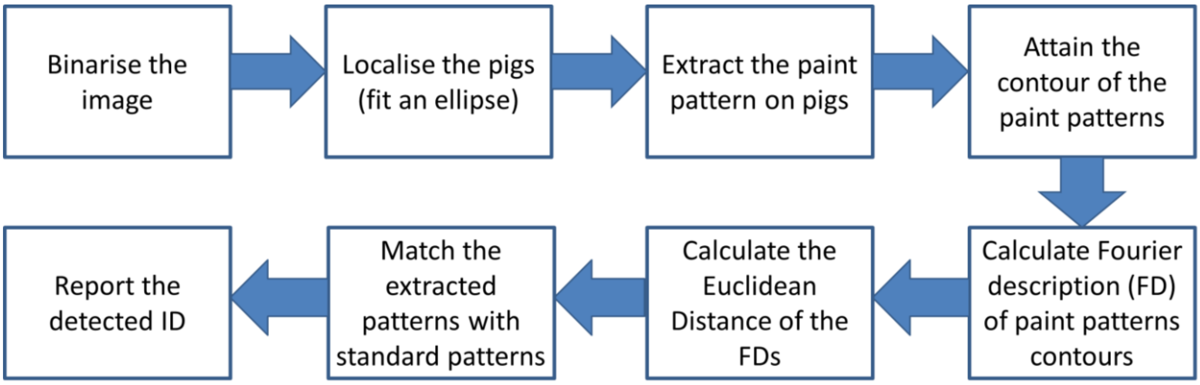


Figure 2-5. Flowchart of identification of marked pigs in a pen

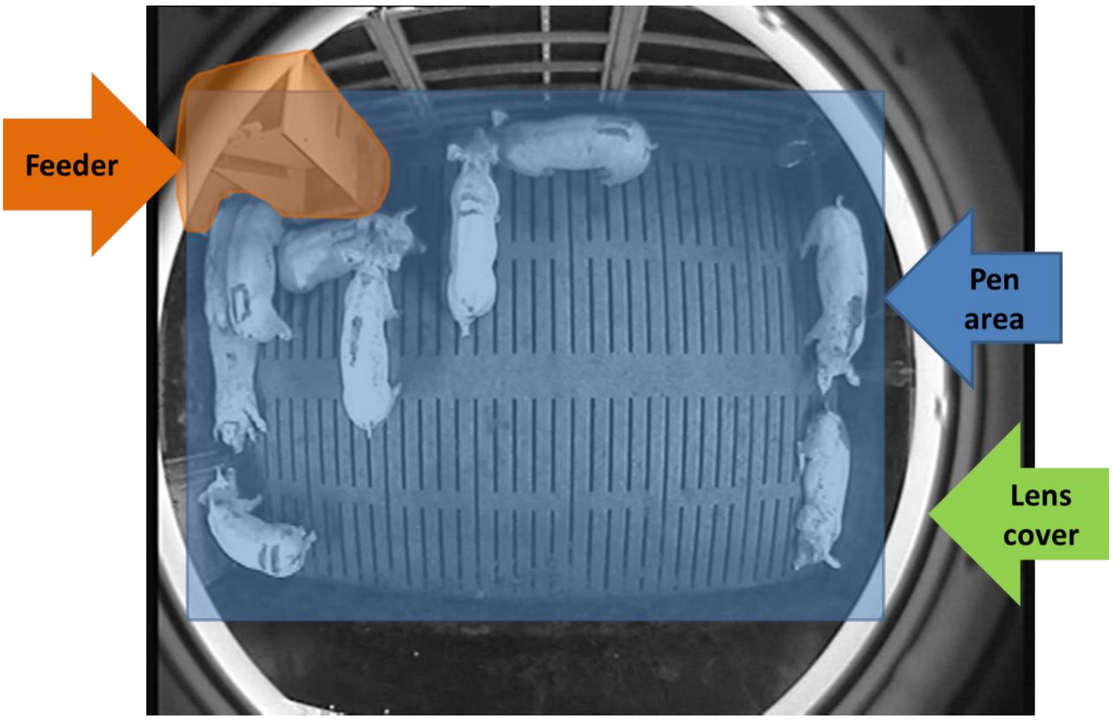


Figure 2-6. Pen floor area and feeder selected by the user

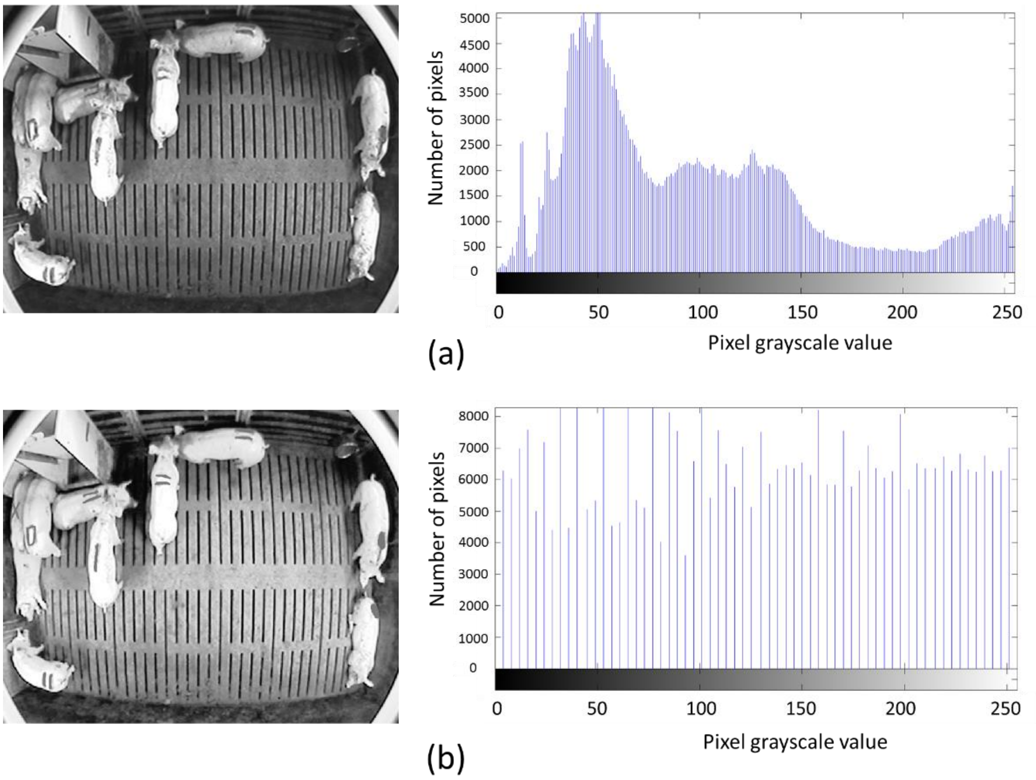


Figure 2-7. a. Original pen image; b. Histogram equalised pen image

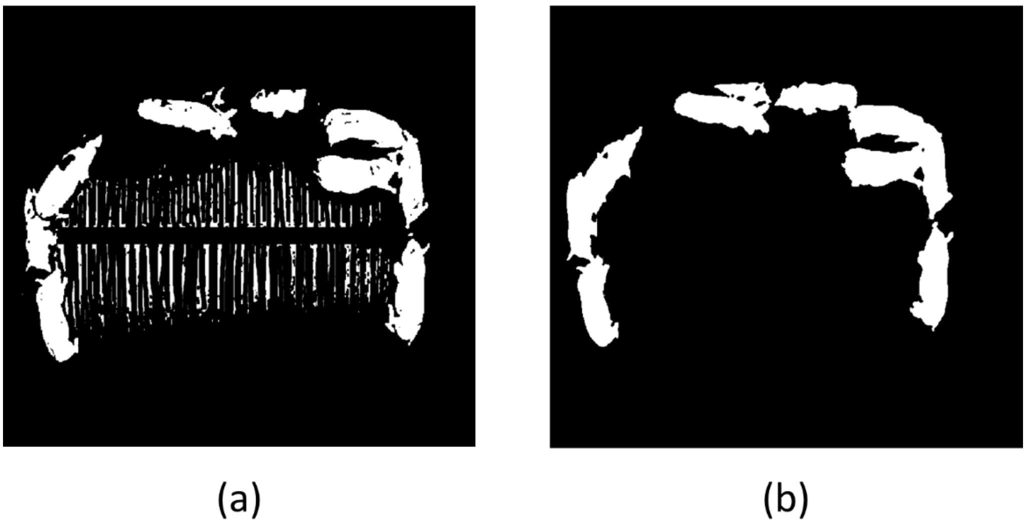


Figure 2-8. Segmented image before (a) and after (b) applying morphological operators

Thereafter the pig's body was extracted as ellipses (Tillett, 1991; Zhang et al., 2005) as bright regions related to pigs had a rather high contrast with the background (pen floor). The procedure for fitting ellipses to the binary image of figure 2-8b was as follows: First, using direct least-squares ellipse-fitting method (Zhang et al., 2005) ellipses were fitted to objects in the image. Subsequently, ellipses parameters such as "Orientation", "Major Axis Length", "Minor Axis Length" and "Centroid" for all objects in the image were calculated. Not to take other shapes in the image mistakenly as pigs, a minimum of 230 and a maximum of 430 pixels for major axis and a minimum of 90 and a maximum of 140 pixels for minor axis of an ellipse were considered. Figure 2-9a illustrates these parameters and figure 2-9b shows the ellipses fitted to the pigs' body (figure 2-8b). It should be noted that in this method it is only important that the area of each floor slit is smaller than a piglet's body area which is practically always the case.

Figure 2-10a and figure 2-10b show a target pattern. For the limited number of pigs in our experiment, the number of identification patterns was limited to five, so each pattern was used for two pigs in a pen, applied either to the front or to the back of pigs' body respectively (figure 2-3). To allow individual identification of pigs who had the same paint pattern (figure 2-3) it was necessary to find where on pigs' body the pattern was painted. This was achieved by painting a triangle on the neck of pigs. The base of the triangle had a distance of mp (figure 2-10a and b) from the centre of the paint pattern. If mp was greater than 40 per cent of the pig body length (np in figure 2-14a and figure 2-14b) IDs 0, 2, 4 and 6 (figure 2-3a, c, e and g) could be detected. On the other hand, IDs 1, 3, 5 and 7 (figure 2-3b, d, f and h) could be verified if mp> 0.6 * np while IDs 8 and 9 were used only once and did not need to be checked with the triangle on the neck. This gave each pig a unique ID. Moreover, the reason why ten unique patterns were not used was that this triangle had applications in other research works carried out based on our experiments. For instance, it was used to analyse animals' movement behaviours such as chasing in which back and front side of pig's body movement is needed to be tracked.

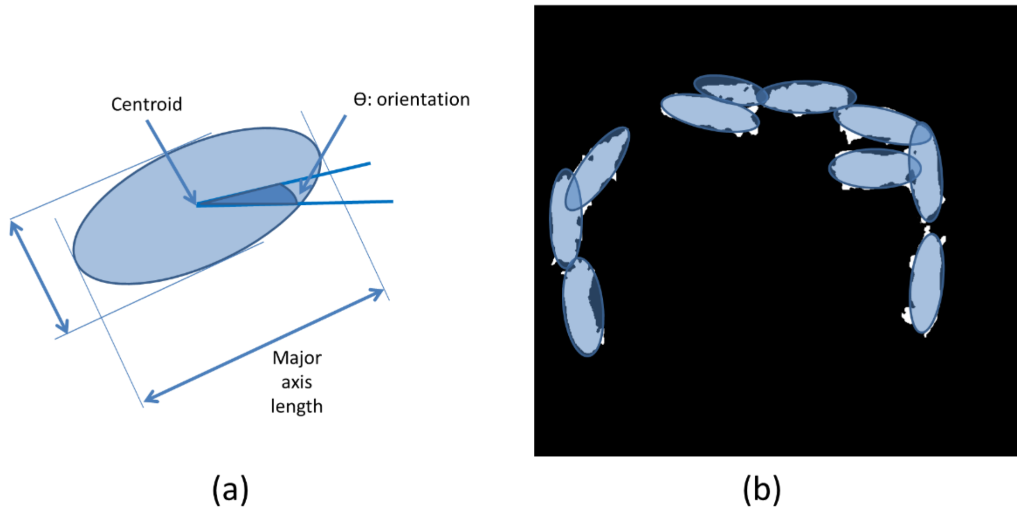


Figure 2-9. a. Ellipse parameters; b. Ellipses fitted to pigs' body

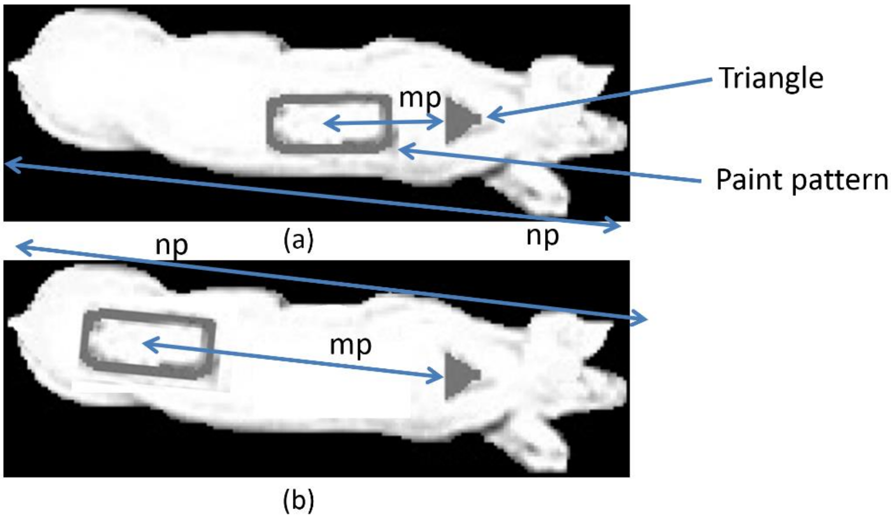


Figure 2-10. a. Location of paint patterns in relation to the triangle painted on neck; For IDs 0, 2, 4: mp>0.4*np; For IDs 1, 3, 5 and 7: mp< 0.4*np

The next step was the extraction of the applied identification pattern on each marked pig. Similar to the extraction of pigs from the binary image, identification pattern on each pig was extracted since the pattern was the biggest dark region on the animal's body with the highest contrast and the pen image's histogram was already equalised. The process of extracting the pattern was as follows: First, similar to localisation of pigs as explained above, a 2-D Gaussian low-pass filter was used and a global threshold was calculated using Otsu's method. Image (figure 2-11a) was binsarised using that threshold resulting in figure 2-11b. Thereafter using the following process, the paint pattern (figure 2-11c) and the triangle (figure 2-11d) were extracted:

1) Connected regions in binary image were identified.

2) Coordinates of connected regions were obtained.

3) The biggest connected region was discovered.

4) A black background image was generated.

5) The region discovered in step 3 was reconstructed on the image generated in step 4.

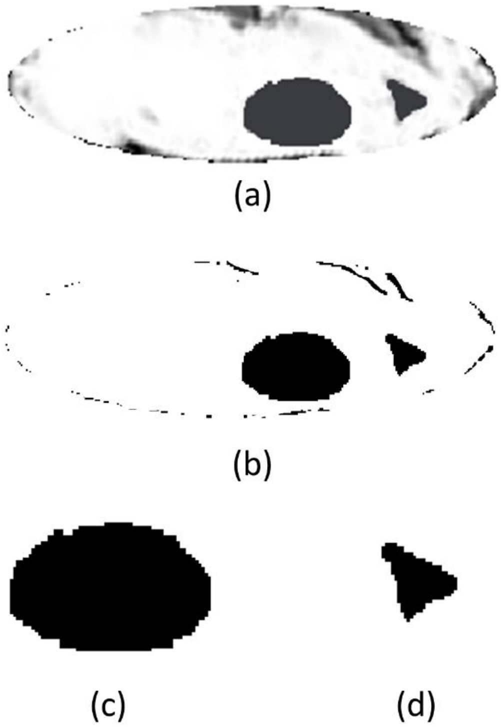


Figure 2-11. a. Pig's body extracted in an ellipse; b. Binarised image of part a; c. extracted paint pattern; d. Triangle for distinguishing repeated patterns

As soon as paint patterns on pigs were located, Fourier transform was applied on the contours of these regions to produce FDs (Kunttu et al., 2005). To attain the contour of these patterns, 2D boundary tracing using the Moore neighbourhood method was applied (Pradhan et al., 2010). In this way, successive coordinates of boundary of paint patterns were obtained.

Since IDs 2, 3, 4 and 5 (figure 2-3) consisted of two split patterns, the boundary tracing algorithm was run twice. In the second run another pattern was sought, ignoring the boundary traced in the first run. The fact that there were two split patterns existing for these IDs, distinguished them from the rest of patterns. Furthermore, based on figure 2-12, depending on the angle between the body direction and patterns (Θ) and ratio of mp to np (figure 2-10) a unique ID could be detected.

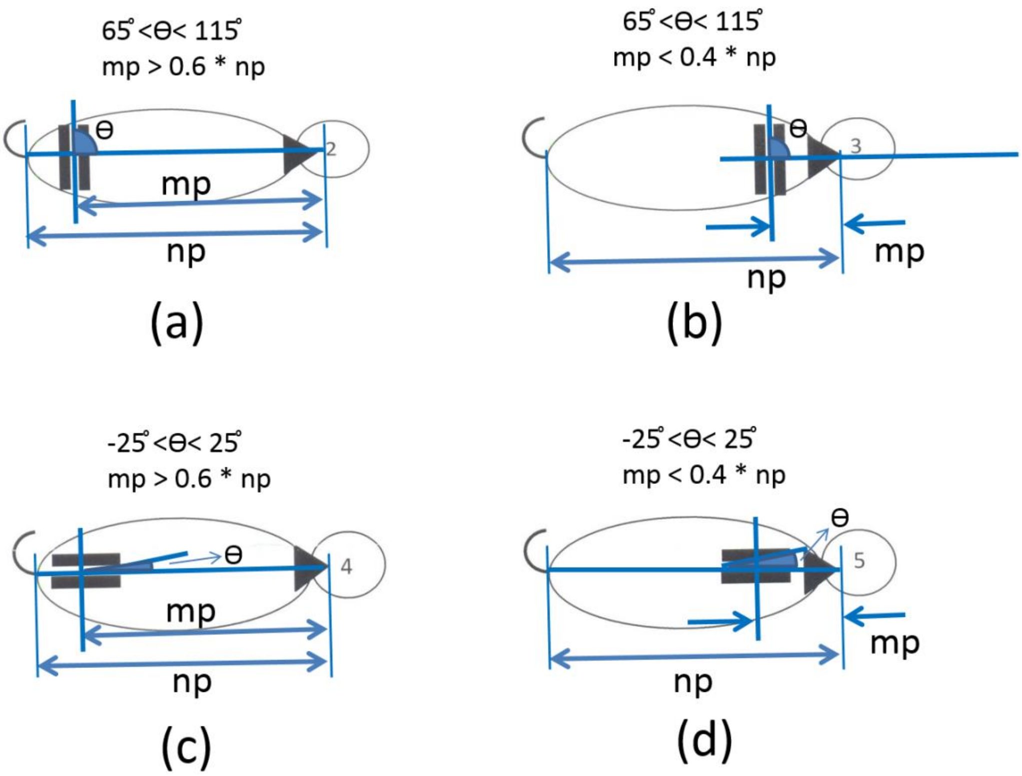


Figure 2-12. Distinction of IDs 2 to 5 (a to d) based on direction and distance of the paint patterns from neck triangle

When the identification pattern coordinates in the image were obtained, FD was used to describe features in the pattern (Zhang, 2002). To achieve a translation and rotation invariance transform, phase information of Fourier coefficients were ignored and only the magnitudes were used. In addition, scale invariance was achieved by dividing the magnitudes by the DC component (Zhang and Lu, 2004).

The similarity between a query pattern P and a target pattern Q was measured by the Euclidean distance (Schwager et al., 2007) between their normalised FD representations derived from equation 2.1.

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \qquad (2.1)$$

In above equation, p and q are FD coefficients of patterns P and Q respectively and n is the number of coefficients considered (here n = 6). In fact, to maximise d (p,q) for different patterns in equation 2.1, many patterns were tested and those with highest Euclidean distance of their FD, namely patterns shown in figure 2-3, were selected. Table 2-1 shows average and standard deviation of Euclidean distance of reference and query patterns.

Table 2-1. Average Euclidean distance of FD of paint patterns for 15600 samples (390 sample per pig per pen); values are shown in this format: Average (standard deviation); For IDs 1, 3, 5 and 7 (repeated patterns) Euclidean distances are the same with IDs 2, 4, 6 and 8 respectively.

Reference pattern / Query pattern							
	Pattern ID	0	2	4	6	8	9
	0	0.0018 (0.0002)	0.1218 (0.0081)	0.1003 (0.0062)	0.0825 (0.0034)	0.0951 (0.0041)	0.1676 (0.0090)
	2	0.1218 (0.0081)	0.0049 (0.0008)	0.0307 (0.0011)	0.1681 (0.0035)	0.2129 (0.0077)	0.0483 (0.0014)
	4	0.1003 (0.0062)	0.0307 (0.0011)	0.0052 (0.0006)	0.1385 (0.0024)	0.1942 (0.0062)	0.1942 (0.0062)
	6	0.0825 (0.0034)	0.1681 (0.0035)	0.1385 (0.0024)	0.0021 (0.0003)	0.1262 (0.0084)	0.2153 (0.0091)
	8	0.0951 (0.0041)	0.2129 (0.0077)	0.1942 (0.0062)	0.1262 (0.0084)	0.0014 (0.0001)	0.2565 (0.0064)
	9	0.1676 (0.0090)	0.0483 (0.0014)	0.0768 (0.0089)	0.2153 (0.0091)	0.2565 (0.0064)	0.0024 (0.0004)

2.3 Results

Following tables show the results of automatic identification of pigs in the experiment carried out for this work. Not all the data were used for validation since manual labelling of the whole experiment data would take a long time.

Table 2-2. Identification of pigs in pen A

Pig ID	Number of samples	Successful identification (Samples)	Successful identification (per cent)	False positive identification (samples)	False positive identification (per cent)
0	390	318	81.54	3	0.8
1	390	342	87.69	6	1.5
2	390	329	84.36	8	2.1
3	390	341	87.44	10	2.6
4	390	316	81.03	3	0.8
5	390	325	83.33	2	0.5
6	390	351	90.00	5	1.3
7	390	326	83.59	0	0.0
8	390	374	95.90	1	0.3
9	390	309	79.23	14	3.6
Total	**3900**	**3331**	**85.4**	**52**	**1.3**

Table 2-3. Identification of pigs in pen B

Pig ID	Number of samples	Successful identification (Samples)	Successful identification (per cent)	False positive identification (samples)	False positive identification (per cent)
0	390	361	87.78	1	0.3
1	390	331	95.56	7	1.8
2	390	326	92.22	4	1.0
3	390	375	85.56	2	0.5
4	390	368	91.11	3	0.8
5	390	381	95.56	1	0.3
6	390	340	91.11	2	0.5
7	390	344	90.00	1	0.3
8	390	329	81.11	6	1.5
9	390	359	93.33	8	2.1
Total	**3900**	**3514**	**90.1**	**35**	**0.9**

Table 2-4. Identification of pigs in pen C

Pig ID	Number of samples	Successful identification (Samples)	Successful identification (per cent)	False positive identification (samples)	False positive identification (per cent)
0	390	351	92.2	1	0.3
1	390	342	96.7	2	0.5
2	390	349	91.1	8	2.1
3	390	365	82.2	4	1.0
4	390	364	84.4	6	1.5
5	390	352	97.8	2	0.5
6	390	333	86.7	0	0.0
7	390	372	93.3	5	1.3
8	390	321	85.6	3	0.8
9	390	351	95.6	12	3.1
Total	**3900**	**3500**	**89.7**	**43**	**1.1**

Table 2-5. Identification of pigs in pen D

Pig ID	Number of samples	Successful identification (Samples)	Successful identification (per cent)	False positive identification (samples)	False positive identification (per cent)
0	390	381	97.7	6	1.5
1	390	308	79.0	4	1.0
2	390	361	92.6	2	0.5
3	390	354	90.8	0	0.0
4	390	344	88.2	2	0.5
5	390	372	95.4	3	0.8
6	390	349	89.5	1	0.3
7	390	361	92.6	2	0.5
8	390	340	87.2	0	0.0
9	390	318	81.5	9	2.3
Total	**3900**	**3488**	**89.4**	**29**	**0.7**

In total, in 42 h data of four pens, 13833 out of 15600 identifications were correctly identified and 159 false positive identifications (1.0%) were recorded. So, with current number of 10 pigs in each pen, automatic identification of pigs could be carried out with an average accuracy of 88.7% while 11.3% were not identified and 1.0% were misidentified. There were a few reasons behind false identifications: 1) Paint patterns were partially faded out over time; 2) Pigs were not always standing in a standard position resulting in unclear paint patterns; Based on data presented in table 2-1, patterns 8 and 0 had the highest (the best) and lowest (the worst) total distance from the other patterns respectively. Therefore, pattern 0 was the least identifiable. In addition, cross identification between patterns 2 and 4 occurred more than between other patterns.

After validating the introduced method, the whole data of the experiment, namely 13 days of recording, 12 h a day and for four pens, individual identification was carried out. In this way they could be tracked and their location in the pen could be determined. To make the tracking results representable, pens were divided to zones as shown in figure 2-13. Attendance of pigs in these zones were monitored and reported in per cent of the total time (156 h) for each pen. Each of these zones relates to a specific behaviour in pigs (Casanovas, 2009). For instance, pigs like to huddle in a corner to sleep. In winter they choose the warmest and in the summer the coolest (Casanovas, 2009). In our experiment the resting zone was at opposite of the feeder zone (figure 2-13). Figure 2-14 shows the individual zone appearance for pen A during the experiment. From this figure one can conclude that in this pen pig no. 2 rested more than others. It should be noted that as soon as pigs lay down their paint pattern will not be visible by the camera anymore and the identification algorithm assumes that the pig is lying in the same spot in which the last time a successful identification was carried out.

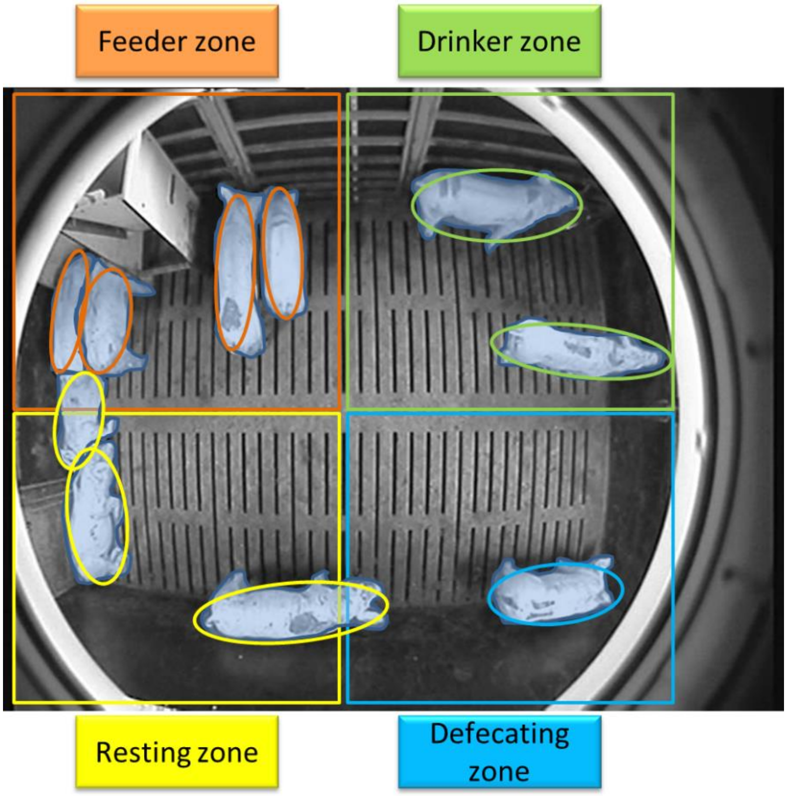


Figure 2-13. Defined zones in a pig pen; pen area was divided to four equal square zones depending on the feeder and drinker location

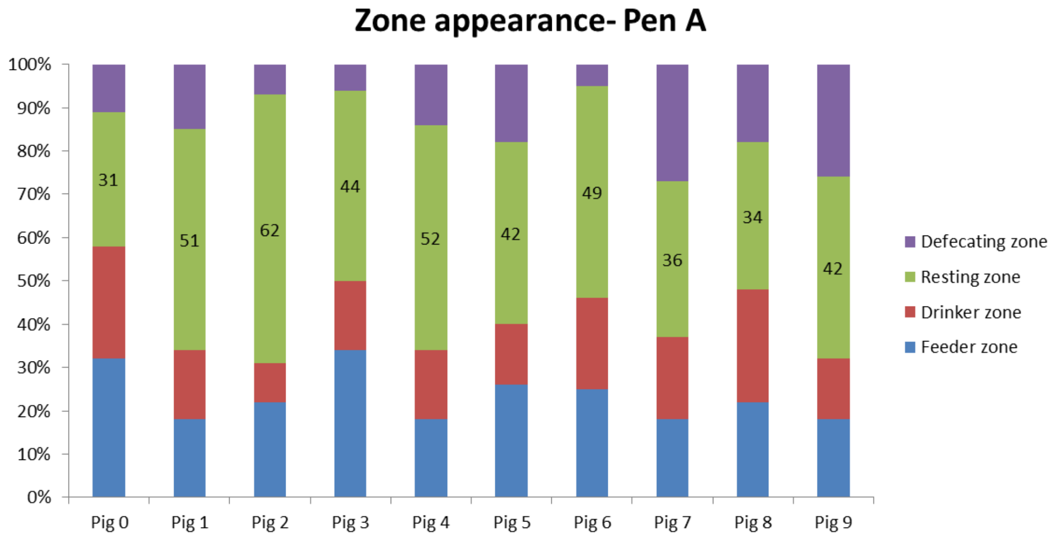


Figure 2-14. Zone appearance of pigs in a pen over 13 days; percentage of appearance in resting zone is indicated.

2.4 Discussion and conclusion

Automatic monitoring of animals is a novel approach and has been applied on many animals (Aydin et al., 2010; Poursaberi et al., 2010; Venter and Hanekom, 2010). Camera technology can be used to monitor every second of animal behaviour. This technology has been mainly practised to study groups of pigs' behaviours (Lind et al., 2005). Observing individual pigs' behaviours is of particular importance since it distinguishes pigs regarding health, aggression and agonistic behaviour (Düpjan, 2009). However, this so far is a visual-manual job.

Identification of pigs is a necessary step towards analysing the different behaviours of pigs individually. Some of the possible applications are calculating the number of times each pig drinks or feeds, how long each pig stays at the drinker or the feeder, how frequent each pig visits the feeder or the drinker, monitoring the trajectory of pigs movement in a pen or analysing individual agonistic behaviours of pigs. Moreover, this can be helpful in monitoring many welfare measures of animals (Botreau et al., 2007) including "body condition" through weight estimation, "functioning of drinkers" through analysing drinking behaviour, "huddling" through analysing resting behaviour, "space allowance" through occupancy analysis and "social behaviour" through monitoring global exploring and group playing. Furthermore, monitoring variables such as individual activity and growth can be automated. For instance, this method can detect unbalanced growth of pigs in a pen that can be due to high competition for food (EFSA, 2007). Therefore, there are many possible applications that can make the use of this technique attractive.

Although methods such as ear tags have been used for identification of pigs (Kitagaki and Shibuya, 2004; Caja et al., 2005), automatic identification of marked pigs in a group by image processing in a pig barn has never been reported in the literature. In this work, an innovative approach using calculating FD of patterns painted on pigs and Euclidean distance of these patterns was chosen to investigate the opportunities of automated identification of marked fattening pigs by vision technology. It was shown that identification of marked pigs in a pen is possible by painting basic patterns on their back and using automated image processing to discern these patterns. This was quite suitable for the purpose of this work since there were dramatic variations in pattern and level of illumination caused by animals' movements and light or angle of view changes. While this method is dependent on contrast between, first, floor and pig skin and second, between pig skin and paint pattern it could still identify pigs in a light intensity range of 11.7 and 176.1 lux with an accuracy of 88.7%.

The paint patterns used in this work were chosen based on Euclidean distance of their FD. Although patterns chosen yielded satisfactory results, these are not the only possible patterns to be used. Authors would suggest 1) to use unified patterns since these can be translated to FD in one single step which makes the pattern recognition process faster; 2) to use paint patterns that are easy to be stamped.

Although it is known that farmers will not paint their pigs for monitoring purposes, this method has been employed to do behavioural analysis and to produce proof of concept. The method allows to do behavioural research on group as well as individual animal level without the need of additional sensors and software. It saves costs and the researchers were able to add functionality to the sensor available (camera). It is certainly a valuable tool for research purposes but we are aware that nowadays this method will be replaced or complemented with a more practical technology. Since identification is one of many functions of the camera used in our design, this algorithm has to be fast enough to be integrated into the monitoring system. Otherwise our monitoring application will not be able to run in real-time. Processing time of all the algorithms developed in this PhD is discussed in section 8.2.1.

This algorithm can help to save many man-hours needed to track pigs manually (Frost et al., 2004) and facilitates detection of behaviours and diseases. For example, it is known that if piglets contract influenza they make 30% less visits to the drink nipple (Bernick, 2007). Using this method it is possible to calculate the number of times each pig visits the drink nipple (Kashiha et al., 2013a) and thus automatically detect a drop in visits. As such, this method offers many potential applications to improve animal husbandry management.

Monitoring behaviours of pigs in a pen is possible both in group and at individual level. Individual level data analysis, however, has more advantages. Individual data analysis allows to assess welfare and health of each animal and this could help to avoid outbreak of diseases or abnormal behaviour of a few pigs affecting the rest of the pen-mates. Therefore, monitoring of individual pigs can give earlier alarms raised by a certain problem.

It is worth mentioning that false positive identification of pigs is unavoidable since they do not always stand in a position in which their patterns are clearly visible. Imperfect and/or poorly visible paint patterns could cause false identification or failure in identifying the pigs. Nevertheless, in the analysis carried out, false positive identification was as low as 1.0% in total while true positive identification was carried out with an accuracy of 88.7%and only 11.3% of IDs could not be identified (false negative).

Finally, behaviours of pigs based on the zone they choose to attend in a pen could also be analysed by the used method. One analysis provided in this chapter was the resting behaviour. Although pigs can rest in any zone within a pen, from manual observations it is known that they rest in more than 96% of cases in the resting zone. Therefore, in this work it was assumed that resting behaviour can be analysed by calculating appearance in resting zone. By combining individual activity and occupancy it would be possible to analyse resting behaviour in other zones as well. This will be investigated in future works. Currently, this method could detect the pigs that rested more than the others. Moreover, there are numerous applications for identification, tracking and locomotion monitoring such as detection of tail biting and aggressive behaviour and analysing posture, activity, drinking, feeding, playing and manipulation behaviour that are possible to be implemented (at least for research purposes) using the presented technique. These possibilities will be investigated in our future work.

In conclusion, the introduced method might contribute in future as a relevant tool in doing research on livestock since feed intake, health, welfare and performance are all variables that are important to be monitored on animal individual level.

Chapter 3 Automatic Monitoring of Pig Locomotion Using Image Analysis

Article title: Automatic Monitoring of Pig Locomotion Using Image Analysis

Authors*: M. Kashiha, C. Bahr, S. Ott, C. Moons, T. Niewold, F. Tuyttens, D. Berckmans*

Source*: Livestock Science, Vol. 159, pp. 141-148*

In chapter 2 the automatic identification of marked pigs in a pen was investigated. This is important because it can distinguish animals from each other based on their individual health status and behaviour. Monitoring of individual animals can result in earlier alarms. This could help to avoid outbreak of diseases or abnormal behaviour of animals affecting the rest of the compartment-mates. Although the current identification technique of non-marked pigs in a pen is a challenge, technology might provide suitable sensors for this purpose in future.

By identifying and localising animals it can be understood how they move in different areas of the animal’s space and how their activity patterns develops.

Activity level of individual animals is a key indicator for their performance and good welfare (Beker Yousuf, 2006). Deviation in activity patterns could be an indicator of pain or lameness in livestock. This deviation is often detectable in locomotion patterns (Anil et al., 2002) and might be detected and reported to the farmer using automated tools, avoiding harm and damage to the animals that may result in a compromised growth. In this chapter monitoring locomotion of individual animals using image analysis is discussed. Therefore, as shown in figure 3-1 we would like to investigate how individual animals in a group move within their living area through measuring locomotion.

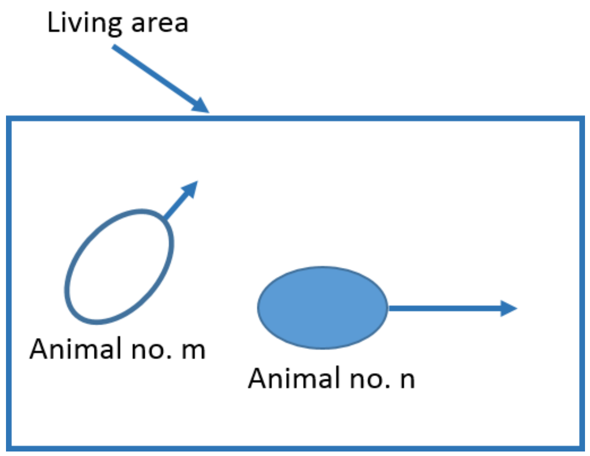


Figure 3-1. Schematic of animals moving within their living area

3.1 Introduction

The increased number of animals per farm has resulted in new welfare problems due to lack of time for individual animal care (HSUS, 2010). Welfare issues can lead to pain and suffering in livestock. This causes stress on livestock and stressed animals can show compromised growth, production and reproduction (Lauber, 2007). Animals experiencing pain normally deviate from their normal behaviour by showing abnormal decreased or increased locomotion (Anil et al., 2002). This deviation can be detected and reported to farmers using automated tools, thus avoiding a compromised growth.

Monitoring locomotion in animals can serve different purposes. Researchers have previously investigated different approaches to monitor locomotion in pigs. For instance, Escalante et al. (2013) fitted sows with a neck collar containing an accelerometer. They used time series of acceleration measurements in order to automatically classify locomotion types which are common among group housed sows. They described five locomotion types: feeding (FE), rooting (RO), walking (WA), lying sternally (LS) and lying laterally (LL). By grouping the locomotion types into active (FE, RO, WA) vs. passive (LS, LL) categories, this method allows them to classify 96% of the active category and 94% of the passive category correctly. It was discussed that this method could be directly employed to automatically detect the onset of oestrus. Another application mentioned involves monitoring the approach of farrowing since the locomotion level of sows is expected to increase during the last 24 h before farrowing (Cornou et al., 2011).

Although earlier studies involved innovative technologies that could be utilised to monitor pig locomotion, many of them require animals to be fitted with sensors or tags. Using these tags raises biosecurity risks (Hernandez-Jover et al., 2008) and pigs endure extreme pain in the installation process (Leslie et al., 2010). Vision-based pig identification technology, however, is a non-intrusive technique that can measure locomotion accurately.

Image processing has also been employed to assess locomotion in livestock. In one study, Lind et al. (2005) introduced a system to automatically track pig locomotor behaviour. They medicated seven pigs varying doses of drugs and quantified locomotion in sessions of 60 min. This method allowed them to track pigs with a repeatability coefficient of 0.6%. The coefficient of repeatability will be low if the variability between the repeated measurements is low. In another study, Cangar et al. (2008) developed an automatic real-time monitoring technique to identify locomotion and posture of eight pregnant cows in the 24 h prior to calving. On average, 85% of standing and lying conditions and 87% of eating and drinking bouts were classified correctly. In addition, existing professional video tracking software can automatically record marked animal locomotion, movement and interaction (Spink et al., 2001).

However, current vision systems need pigs to walk in front of the camera one by one (Lind et al., 2005) or to be marked (Noldus et al., 2001; Kashiha et al., 2013b). Because of this, they can only provide locomotion for the animals as a group (Costa, 2007). The disadvantage of the latter is that variation in locomotion between pigs cannot be measured.

The objective of this study is to monitor individual pig's locomotion in a group of 10 individual animals through automated quantification of locomotion levels under experimental conditions using continuous image analysis.

3.2 Materials and Methods

3.2.1 Animals and housing

This section is identical to section 2.2.1.

3.2.2 Equipment and data collection

This section is identical to section 2.2.2.

3.2.3 Development of the automated locomotion quantification protocol

The processing flowchart to monitor locomotion in a pen is shown in figure 3-2. First, for each pen, the feeder and the pen floor area were initially determined manually. The feeder needed to be excluded from the image since it could affect the segmentation accuracy. In addition, the pen floor had to be excluded to eliminate the camera cover appearing in the segmented image (see figure 2-6). To eliminate light effects, the histogram of the image was then equalised using adaptive histogram equalisation (Sherrier and Johnson, 1987).

In a second step, each image was binarised to eliminate the background. Thirdly, each image was segmented in order to find the location of the pigs. Details of these processing steps were explained in section 2.2.3.

Steps shown in figure 3-2 are explained in the sections below.

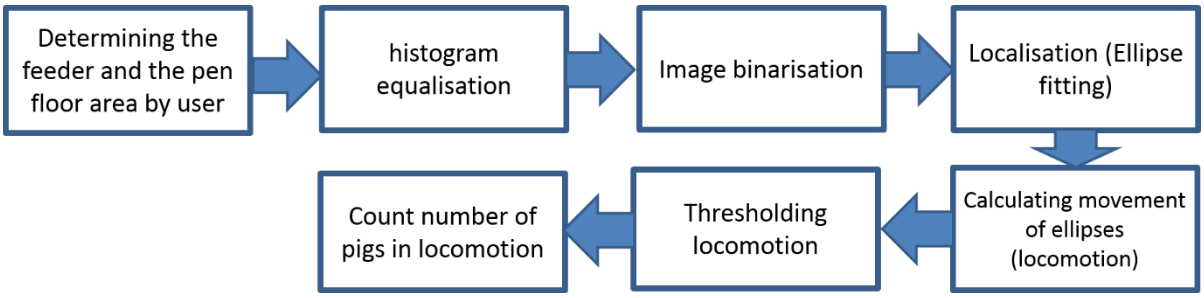


Figure 3-2. Image processing flowchart to monitor locomotion in a pen

3.2.3.1 Image Locomotion

Image Locomotion (ImL) is defined as the amount of movement an object produces in pixels. Using the ellipse models presented in the previous section, ImL is mathematically explained as shown in equation 3.1. ImL is composed of two steps: 1) Angular motion (moving from ellipse E_1 to E_2 in Figure 3-3), in meter * pixel; 2) Linear motion (moving from ellipse E_2 to E_3 in figure 3-3), in meter * pixel; To make ImL independent from pig body size, it has to be divided to body length (L).

$$ImL = \frac{|Linearmotion|+|angularmotion|}{L} = \frac{|\vec{T}|+\left|(\measuredangle\vec{T})*\frac{L}{2}\right|}{L} = \frac{T}{L} + \frac{\tan(\theta_T+\theta_1)}{2} \qquad (3.1)$$

Where:

ImL is the Image Locomotion; in pixels

$\vec{T}$ is the movement vector (from ellipse E_1 to ellipse E_2); in pixels

$T = |\vec{T}|$ is the size of the movement vector; in pixels

θ_T is the difference of orientation between ellipses E_1 and E_2; unit-less

L is average of size of the major axis of ellipses E_1 and E_2. This is equal to body length of a pig; in pixels

$\measuredangle$ is the angle operator

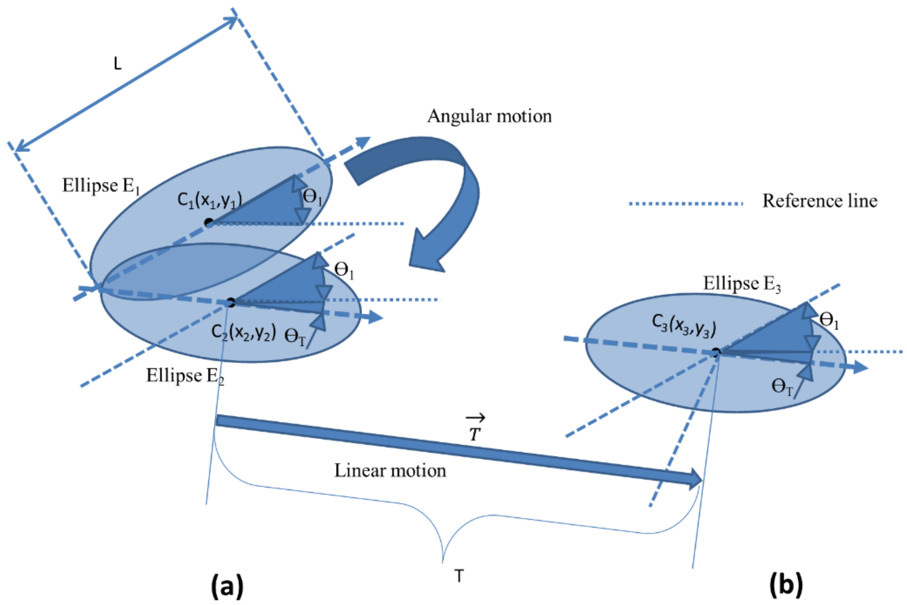


Figure 3-3. Ellipse fitted to pig's image: (a) at time "t-1"; (b) at time "t"; T is the distance travelled;

3.2.3.2 Image Locomotion Detection

ImL was monitored over time and Image Locomotion Status (ImLS) was determined based on the following parameter:

$$ImLS = \frac{ImL}{L} \qquad (3.2)$$

Where:

$ImLS$ is the Image Locomotion Status; unit-less

ImL is the Image Locomotion; in pixels

L is the average size of the major axis of ellipses E_1 and E_2 (figure 3-3); in pixels

The next step was to decide, based on ImLS, whether a pig was In Locomotion (IL) or Not In Locomotion (NIL). Based on the *ImLS* parameter and an experimental *ImLS* threshold of 0.4, pigs were categorised as NIL if *ImLS* ≤ 0.4 or as IL if *ImLS*> 0.4. This means if a pig moves more than 40% of his body length (L in equation 3.1), it is considered to be IL. Otherwise he is NIL.

3.2.3.3 Manual labelling

As a reference, the manual "labelling" of recorded videos was done by an ethologist experienced in labelling. Human visual observations of the pig's behavioural locomotion were performed offline on videos using 2-min instantaneous scan-sampling in four 30-min sessions on 6 selected days. Preliminary observations allowed for the selection of two morning sessions (session 1: 09.30-10.00 h and session 2: 11.00-11.30 h) and two afternoon sessions (session 3: 16.00-16.30 h and session 4: 17.30-18.00 h), to compare automated with manually labelled behavioural locomotion. The behaviour of each individual pig was labelled using the Observer XT 10.2 software (Noldus, Wageningen, The Netherlands). 4*15 or 60 scan samples per pig per day were obtained. For each scan sample, all 10 individual pigs of one pen were scored as either IL or NIL. Locomotion behaviour was defined as walking, running, and/or performing other behavioural activities such as exploring or manipulating pen fixtures, manipulating pen mates, agonistic behaviour, feeding, drinking, or other behavioural activities that include physical movements of any body part. Accuracy of this method is 5 cm. If a pig was not performing behaviours of the "In Locomotion" behavioural category it was considered Not In Locomotion. Finally, the number of IL pigs was tallied, to calculate the number of IL pigs per pen.

6 (days) * 4 (30-min) * 15 (scan samples) or 3600 scan samples out of 13 (days) * 12 (h) * 3600 (seconds) * 10 (pigs) or 5.616 million frames were used for validation and the rest of data were analysed by Image Locomotion Detection technique introduced above.

3.3 Results

3.3.1 Validation

In order to validate the automated image processing technique, image detected locomotion was compared with labelling results, as shown in table 3-1. There were 24x 30 min intervals, each of which consisted of 15 scan samples. In each of these scan samples, 10 pigs were scored for their locomotion, which means that in total there were 6 (days) * 4 (sessions) * 15 (scan samples) * 10 (pigs) or 3600 scan samples per pen. In total, 14400 frames were analysed, which were recorded from four pens.

Table 3-1. Locomotion in 4 pens, comparing labelling and automated image analysis

		Labelling-IL	**Image analysis-IL**		
Pen	Scan samples	scan sample	True positives (Sensitivity)	False positives	False negatives
1	3600	1515	1432 (94.5%)	48 (3.2%)	83 (5.5%)
2	3600	1343	1209 (90.0%)	21 (1.6%)	134 (10.0%)
3	3600	1316	1131 (85.9%)	61 (4.6%)	185 (14.1%)
4	3600	1722	1525 (88.6%)	32 (1.9%)	197 (11.4%)
Total	14400	5896	5297 (89.8%)	162 (2.7%)	599 (10.2%)

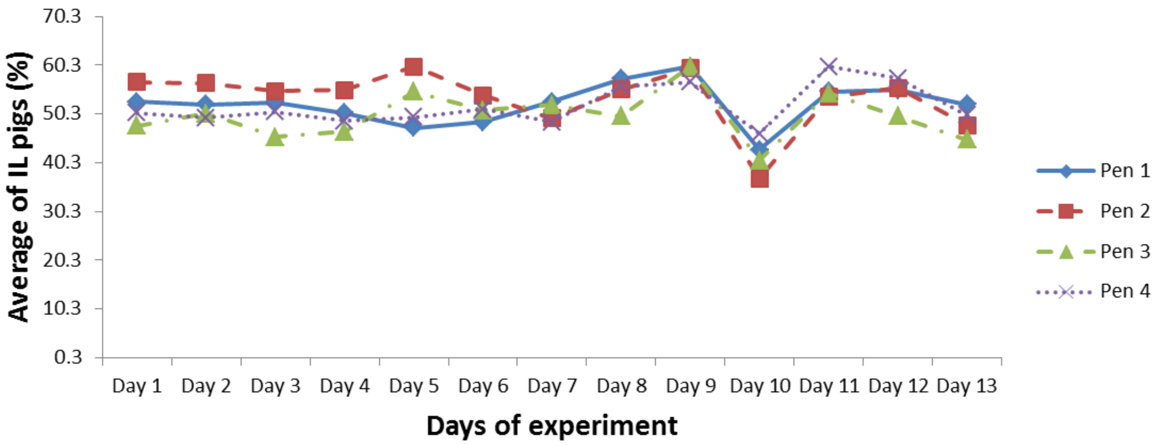


Figure 3-4. Average percentage of IL pigs during 13 days of the experiment detected by ImLS algorithm

Out of 5896 IL pigs, 5297 were identified correctly, while 162 False Positive (FP) identifications (2.7%) and 599 False Negative (FN) identifications (10.2%) were recorded. This leads to an overall accuracy (=sensitivity) of 89.8% for a stocking density of 1.23 pig/m^2.

3.3.2 Continuous data analysis

After validating the method, all 13 days of the experiment data were analysed. There were in total 5.616 million (432000 per day) scan samples per pen to analyse. Figure 3-4 shows the average of IL pigs per pen during the days of the experiment.

3.4 Discussion and conclusion

Automatic monitoring of animals has been tested with many different species (Venter and Hanekom, 2010; Brendle and Hoy, 2011). Moreover, for farm managers this technology seems promising for monitoring purposes, mainly thanks to the broad applications automated animal monitoring has to offer. Camera technology, in particular, has made it possible to monitor animal behaviour at each second and has also proved especially suitable to study group behaviour (Pastorelli et al., 2006). Authors previously showed that this technology can be helpful for tracking and identifying pigs (Kashiha et al., 2013b) for monitoring behaviours. In the current study one of these important behaviours, namely locomotion, was quantified.

Reliable results achieved in this work open the way to further behaviour analysis using automated image analysis.

Monitoring animal locomotion in groups is an essential aspect of analysing different behaviours. Some of the more specific behavioural aspects that can be focused on are locomotor behaviour (Lepron et al., 2007), lameness detection(Kramer et al., 2009), agonistic behaviour (Szendrő and Dalle Zotte, 2011) and freezing behaviour (Vanheukelom et al., 2012). Moreover, this technology can help to monitor a large number of welfare measures taken to improve the animals' wellbeing (Botreau et al., 2007), such as "ease of movement" and "thermal comfort". Hence, there are many possible applications for which the use of this technique can be attractive.

Although markings have been used to monitor pig locomotion in previous studies (Noldus et al., 2002; Spinka et al., 2004), automatic detection of the locomotion of unmarked pigs in a group by image processing has never been reported in the literature. The existing techniques require marking colour (Spinka et al., 2004) on pigs. In this study, however, an innovative approach using movement calculation of ellipses fitted to pigs' bodies was chosen to investigate the possibilities of automated locomotion detection for fattening pigs using vision technology. It was found that pig locomotion detection is possible by localising individual pigs in the group by fitting ellipses onto their topview body image and tracking those ellipses over time.

Among the previous methods used for pig locomotion monitoring, the moving pixels calculation method used in eYeNamic tool was the most successful (Leroy et al., 2006). This tool calculates the difference in image intensity between consecutive frames. From this difference image, the binary 'locomotion image' $I_a(x, y, t)$ is derived, containing the pixels for which the intensity change exceeded a certain threshold. A summation of the number of these pixels yields the total amount of locomotion at time t (figure 3-5). As this technique has been the most successful to date, it might be interesting to examine how it compares to the method proposed in this study. Since eYeNamic cannot determine the number of IL pigs, one development phase was launched to determine a threshold for number of pixels to decide how many pigs in a pen were IL. In the validation phase, data presented in table 3-1 were also analysed with eYeNamic. Table 3-2 shows the results of this comparison. Upon these results ImLS method reports 10.2% of FNs in detecting number of IL pigs while eYeNamic categorises locomotion of pigs with a FN rate of 39.2%. In addition, FPs were 2.7% and 11.8% respectively. Thus, ImLS method yields a higher accuracy in detecting locomotion of pigs.

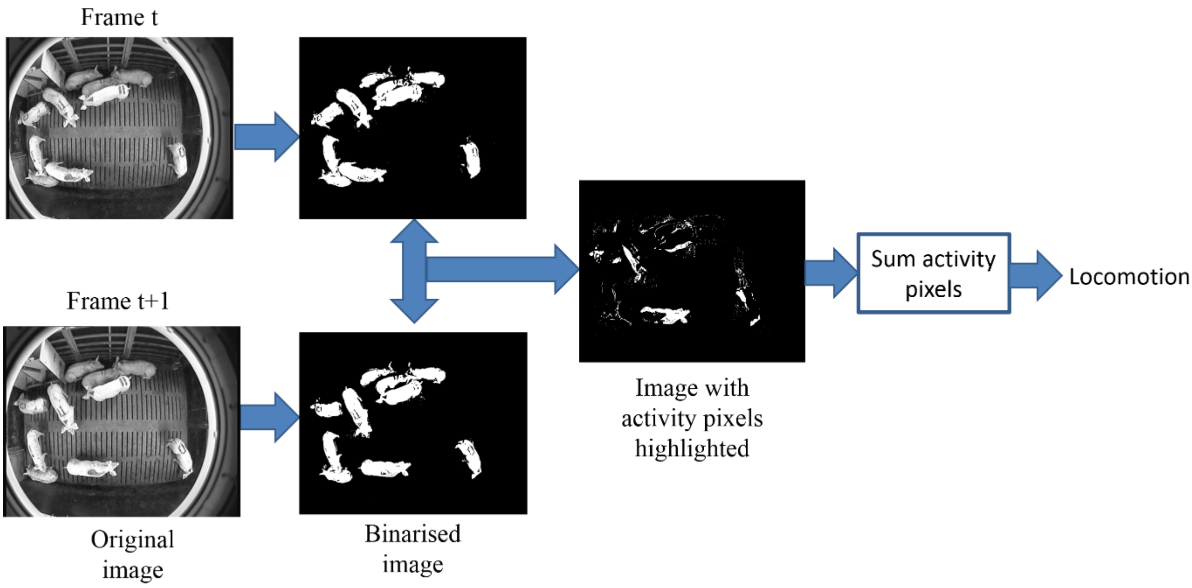


Figure 3-5. Locomotion calculation using eYeNamic tool

Table 3-2. Comparison of labelling, ImLS technique and eYeNamic tool in detecting number of IL pigs in a pen (NIL includes standing and lying; IL includes running and walking)

			Labelling	**Image analysis**		**Image analysis**	
Pen	Scan samples	IL	Average of active pigs in pen (out of 10)	ImLS	False Negatives = |IL-ImLS|	By eYeNamic (eYe)	False Negatives = |IL-eYe|
1	3600	1515	4.2	1432	83 (5.5%)	1042	473 (31.2%)
2	3600	1343	3.7	1209	134 (10.0%)	1851	508 (37.8%)
3	3600	1316	3.6	1131	185 (14.1%)	891	425 (32.3%)
4	3600	1722	4.9	1525	197 (11.4%)	2640	918 (53.3%)
Total	14400	5896	4.1	5297	599 (10.2%)	6424	2324 (39.4%)

The introduced technique was robust against body shape variations in standing and lying position. This made it quite suitable for the purpose of this study since there was a considerable variation in brightness between pigs' different postures and locations. It is worth mentioning that the occurrence of FPs and FNs in detection of locomotion is unavoidable. Incorrect classification (FP) or failure in classification (FN) were due to several factors: 1) Segmentation was often an issue in resting zone since pigs tended to lie down socially (in contact with each other and sometimes with some overlapping) thereby complicating the segmentation task; 2) there were sometimes mistakes in labelling IL pigs by observers due to overlapping of pigs, eye errors or a false judgement for pigs with average locomotor behaviour; Nevertheless, while this method is dependent on contrast between floor and pig surface it could still detect IL pigs in a light intensity range of 11.7 and 176.1 lux with an accuracy of 89.8%.

Although this method would theoretically work with a wide range of light intensity and contrast between pigs and floor, background subtraction and segmentation of pigs' bodies can be a challenge. Therefore, authors would suggest setting the ImLS threshold using the data of the day before. This means at the end of a day, ImLS threshold ($ImLS^T$) is calculated to be used on the day after. Threshold of today is calculated using the equation below:

$$ImLS^T = \text{median}\,(ImL^Y) \tag{3.3}$$

Where:

$ImLS^T$ is the Image Locomotion Status Threshold for today

ImL^Y is the Image Locomotion of pigs for yesterday

The method allows doing behavioural research at group level without the need of additional sensors and software and without the need to mark the animals (for tracking purposes), or to interfere with them in any other way. It saves costs and makes researchers able to add functionality to video cameras. It is certainly a valuable tool for research purposes and has an advantage of being non-intrusive. In addition, since measuring locomotion is one of many functions of the camera used in our design, this algorithm has to be fast enough to be integrated into the monitoring system. Otherwise our monitoring application will not be able to run in real-time. Processing time of all the algorithms developed in this PhD is discussed in section 8.2.1.

Combining this method with identification techniques such as using ear tags (Allen et al., 2008), animal husbandry management can be improved. However, there are still challenges to use the proposed technique in practical settings. Due to experimental requirements, stocking density in images used in this study was as low as 1.23 pig/m^2 while in a real farm setting, stocking density will be as high as 1.67 pig/m^2 (Schinkel et al., 2009). The higher the stocking density, the more difficult segmenting the pigs in the image will be. This could in turn have a negative effect on accuracy of locomotion detection. One way to address this problem is to calculate locomotion by comparing consecutive frames (Leroy et al., 2006).

Locomotion monitoring can have many applications such as stressor response analysis. By combining locomotion with other parameters such as occupancy which is calculated by dividing the total number of object pixels, relative to the total number of pixels in a given area, one could analyse pigs' behaviours including playing, resting, drinking, feeding and manipulation behaviour. These possibilities will be investigated in future work.

In conclusion, this method, which can measure locomotion with an accuracy of 89.8% might contribute in the future as a practical tool in livestock husbandry since health, welfare and performance are all variables that are related to improving locomotion.

Chapter 4 Performance of an Image Analysis Processing System for Hen Tracking in an Environmental Preference Chamber

Article title: Performance of an Image Analysis Processing System for Hen Tracking in an Environmental Preference Chamber

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Monitoring locomotion of individual animals in groups is an essential aspect of analysing different behaviours. The reason why the animal attends a certain zone is very relevant to the animal's behaviour; hence, interpreting information such as animal locomotion and occupancy of a certain zone can lead to an improved assessment of welfare and health.

A better way to understand and interpret animal behaviour is the use of choice and preference tests (Kirkden and Pajor, 2006; Scholz et al., 2010). Figure 4-1 shows a schematic of a sample preference test where an animal prefers a certain zone within its living area. This evolves from the idea of investigating how animals move within their living area (figure 3-1).

This chapter discusses how animals will behave when given choices to move between pen zones with different environmental conditions. In a case study, laying hens were monitored while moving between compartments with different ammonia concentrations. Elevated ammonia concentrations over a few days can cause a significant loss in egg production (Cotterill and Nordskog, 1954; Garner et al., 2012; Leinonen et al., 2014) and it is assumed that if the performance of the animals can be compromised by high ammonia concentrations, the effect will also show in animal behaviour. Therefore, it is important to understand how and why different ammonia levels could affect animal's activity and zone occupancy.

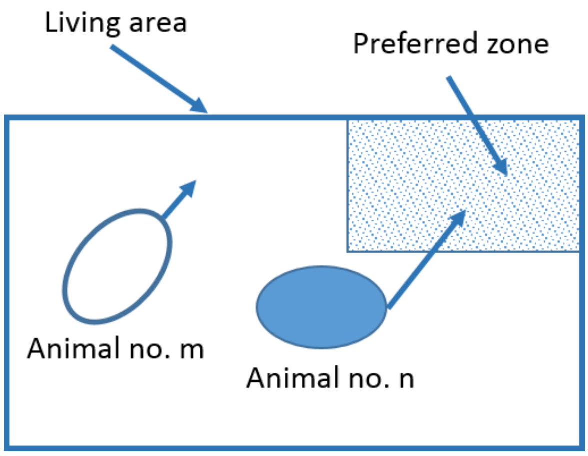

Figure 4-1. Schematic of animals preferring a certain zone in their living area

4.1 Introduction

Conventionally, an extensive list of welfare indicators is used to assess welfare of livestock (Duncan, 1981). Recently, however, many scientists argue that instead of such a list and giving each indicator the same weight, one should directly focus on health and needs of animals (Dawkins, 2004). In addition, it is known that behaviour could perform a major role in dealing with the two above issues. Behaviour is used to assess health through the clinical and pre-clinical assessment of pain, injury and disease. It also is truly important in gauging what animals' needs are. This is not only carried out through on-farm assessment, but also through the use of choice and preference tests (Kirkden and Pajor, 2006; Scholz et al., 2010). Role of behaviour analysis could be more prominent if used in conjunction with new technology.

In recent years, Image Processing Technology has been practised for animal tracking purposes throughout the world (Sergeant et al., 1998). With the growing need for quality control and animal welfare management, the demand for automatic animal identification and behaviour monitoring as well as traceability has increased. According to (Schofield et al., 1999), image processing systems have been used for the production market, but more specialised research systems are needed to track animal behaviour in research studies with custom animal housing and specific data collection requirements (Lay et al., 2011).

Image processing technology is widely used in PLF and in supply chain management to identify (Kashiha et al., 2013b), track (Kashiha et al., 2014), and monitor behaviour and health status of agricultural animals (Yang et al., 2010; Kashiha et al., 2013c). Image processing systems are comprised of a camera connected to a PC via a capture card. Captured videos are then encoded and recorded on an external hard drive. These videos are subsequently decoded and analysed.

The use of image processing technology has been extended to animal behaviour and welfare research because it offers tools to monitor and to obtain feedback on animal location and resource utilisation. For instance, image processing tracking systems have been proved as effective to monitor animal feeding and/or drinking behaviour (Kashiha et al., 2013a), growth (De Wet et al., 2003) and activity (Leroy et al., 2006; Calvet et al., 2009).

One of the common approaches in monitoring animal behaviour is a choice test. In choice-tests, animals are provided with multiple choices among situations or resources. The choices must be registered to determine animal preferences. Identifying animal location (choice made) and time spent at that particular location is essential for assessment of environmental preferences. Choice-tests as applied in animal behaviour and welfare research may benefit from the use of leading-edge technology. Researchers previously used Radio Frequency IDentification (RFID) to monitor animals when they had to choose between available compartments. Sales (2012) implemented and evaluated such system for its use in an Environmental animal Preference Chamber (EPC) to detect hens transiting between compartments of the EPC. The system faced difficulties since their RFID system detection range did not cover the entire test bird area, conflicts were caused by multiple RFID tags within the same detection zone and visits shorter than the RFID antenna scan interval could not be detected. In another study, Green et al. (2008) developed an EPC to assess responses of laboratory mice to atmospheric ammonia. They used infrared sensors for automatic tracking of mouse movements. Infrared tracking was sufficient for summarizing group behaviour, but ineffective in recognizing individual mice and required a backup video system to verify their data. More recently, image processing-based tracking methods have been used in tracking animals subjected with choice-tests (Straw et al., 2011). Accordingly, objectives of this study were based on employing image processing technology in tracking layers during choice tests.

The objective in this study was to evaluate the performance of an image processing system applied within a stainless-steel EPC for poultry, by performing the following tasks:

- Tracking hen navigation through detection of a hen navigating the compartments.
- Comparing this to Human Video Observations to identify potential image processing misdetections and their causes.
- Validating choice-test study positioning data, which consisted of collecting occupancy data and videos from a choice-test study with a bird and comparing the detected events.

The above system can have many applications for monitoring laying hens' behaviours. An immediate example for this is ammonia aversion (Sales, 2012). In periods of extremely cold weather, energy conservation in a laying house usually results in a restricted ventilation rate (Deaton et al., 1982) and an increase in air pollutants particularly ammonia (Deaton et al., 1984). Hens can lose a significant amount of weight with a reduced feed intake caused by elevated ammonia concentrations (Kristensen and Wathes, 2000). Moreover, previous studies through manual observations showed that laying hens significantly preferred fresh air (approximately 0 Part Per Million by volume (ppm_v) to an ammoniated atmosphere (Deaton et al., 1982).

An image analysis system was tested to investigate ammonia aversion by laying hens through monitoring compartment occupancy. This is based on the hypothesis that hens tend to prefer compartments with lower ammonia concentration and avoid those with higher concentrations.

4.2 Materials and methods

4.2.1 Environmental Preference Chamber

An EPC comprised of four stainless steel compartments (1.2 m x 1.2 m x 1.2 m occupancy space, with conical subfloor and attic space) was located at the Environmental Research Laboratory of the University of Illinois at Urbana-Champaign, USA. Further details on the design, development, and operation of the EPC have been documented by Sales (2012) and Sales et al. (2013)[1].

The four EPC compartments were interconnected by passageways which allowed a test bird to walk from one compartment to either of the adjacent ones. A video camera was mounted from each cage's ceiling above the bird area in the centre at a height of 46 cm. These cameras captured

[1] Experiments were conducted in accordance with the principles and guidelines presented in Guide for the Care and Use of Agricultural Animals in Research and Teaching, 3rd edition, 2010 (Association Headquarters, Champaign, IL 61822)

video of the compartments for 16 days. They were equipped with a motion detection system. This system replaced a compartment image with no pixel movement with a blank screen as illustrated at right side of figure 4-2a. Setup is shown in figure 4-2b, and hardware information of the cameras is provided in the next section. There were four cameras and four images which were stitched as shown in figure 4-3a.

4.2.2 Image acquisition system

An animal tracking system based on image processing technology was added to the EPC to automatically and continuously determine where a bird was located. The purposes of this system were to record a single hen at a certain compartment, to be capable of operating in harsh environments, and to be built at a relatively low cost. Thus, the system was comprised of the following elements:

- A commercial surveillance vision system (Geovision GV-1240A D-Type Combo Card, Geovision, Inc., Taipei, Taiwan) including four colour mini dome analogue cameras (Aventura, CAM-5D-24DN-VP) with a 2.4 mm fixed lens; these are weather-proof (IP66) and Vandal-Proof. Camera resolution was 550 TeleVision Line (TVL) at day and 600 TVL at night
- A four-channel VNS-04 Analogue to IP[1] Camera Encoder produced by Aventura, recording rate of 30 fps, maximum resolution of 704x480 pixels, Moving Pictures Experts Group four (MPEG4) / H264 compression
- Geovision RemoteViewlog[2] software for merging, tiling and decoding recorded video files
- Matrix Laboratory (MATLAB) software (2013a version, Mathworks, Natick, Massachusetts, United States) for video analysis

4.2.3 Video set description

In total 16 (days) x eight (h; average of events per day) x 3,600 (seconds in one hour) = 460800 frames were considered for continuous data analysis. Out of this video set, 20 (sessions) x 30 (min per session) x 60 (seconds in a min) or 36000 scan samples were obtained and used for algorithm development. This represented a rate of 7.8% of labelling. Section 4.2.7 explains how these labelling sessions were chosen.

[1] Internet Protocol
[2] http://www.geovision.com.tw/english/5_8.asp#

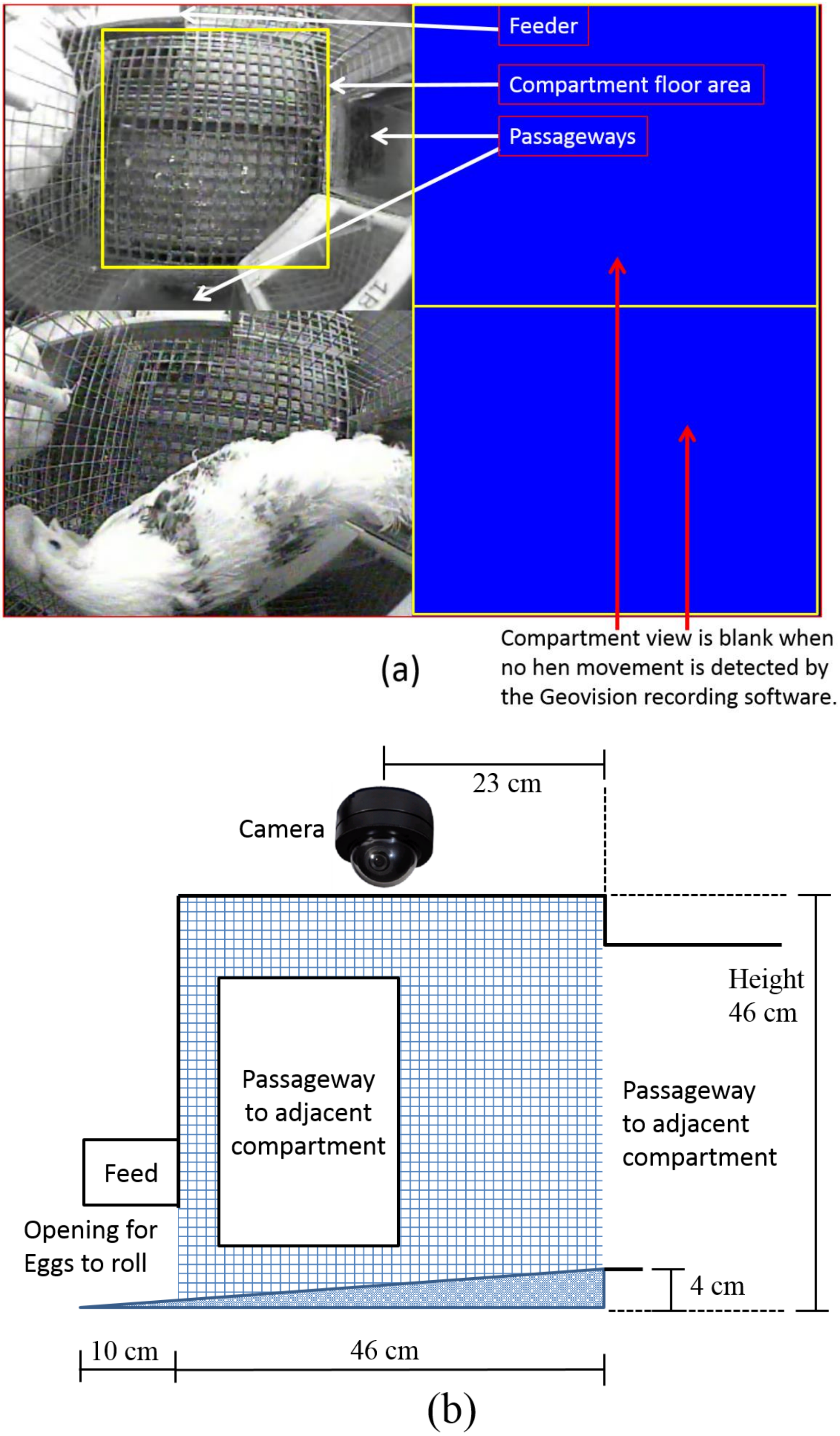

Figure 4-2. a. Screenshot of the EPC video monitoring system; b. Cross-section of a cage showing side view of the test bird area with access to two passageways.

4.2.4 Tracking hen navigation

In order to detect the hen in a compartment, captured frames were analysed offline using MATLAB, using the Image Processing System (IPS). The main task for this IPS was to eliminate the background and to extract topview hen body through image binarisation. The binarisation procedure was implemented as follows: 1) The image was filtered using a two-dimensional (2D) Gaussian low-pass filter; 2) A global threshold was calculated using Otsu's method (Otsu, 1979); 3) The image (figure 4-3a) was subsequently equipped with a hard threshold resulting in figure 4-3b; 4) To remove small objects such as compartment grid and edges from the image, a morphological closing operator using a disk-shaped structuring element with a size of 10 pixels (Gonzalez and Woods, 2001) was subsequently applied. The morphological closing operation consists of dilation followed by erosion, using the same structuring element for both operations. Conducting this operation resulted in figure 4-3c.

Next, each image was segmented in order to determine the location of the hen. To segment the image, the hen body was extracted as an ellipse (Zhang et al., 2005) within each pen. The procedure for fitting ellipses to the binary image as displayed in Figure 4-3c was as follows: 1) Using the direct least squares ellipse-fitting method (Zhang et al., 2005), ellipses were fitted to objects in the image; 2) Ellipse parameters such as "Orientation", "Major Axis Length", "Minor Axis Length" and "Centroid" were calculated for all objects located in the image. To avoid incorrectly identifying other shapes in the pen as birds, a minimum of 360 or 150 pixels and a maximum of 80 or 30 pixels were considered for the major and minor axes of an ellipse, respectively. A hen entering or exiting a compartment was detected using the above thresholds. Figure 4-4a illustrates these parameters and figure 4-4b shows the ellipse fitted to the hen body.

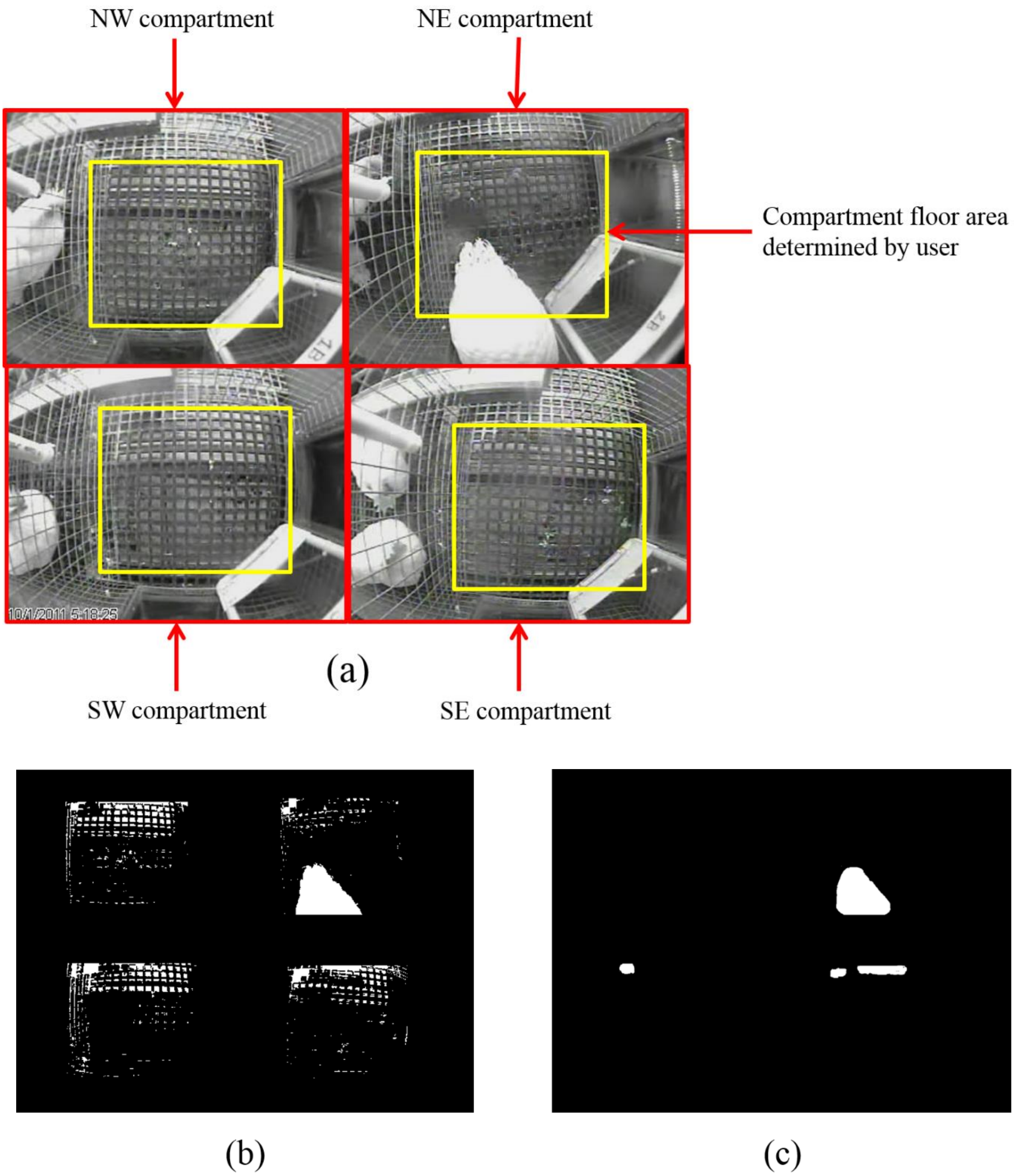

Figure 4-3. Topview image of the EPC, NW stands for North West, NE stands for North East, SW stands for South West and SE stands for South East; Birds to left of each compartment are companion birds (not included in analysis), and the single test bird is partially visible in the NE compartment. B. binarised version of part “a”; c. binarised image (part b) after applying morphological operators

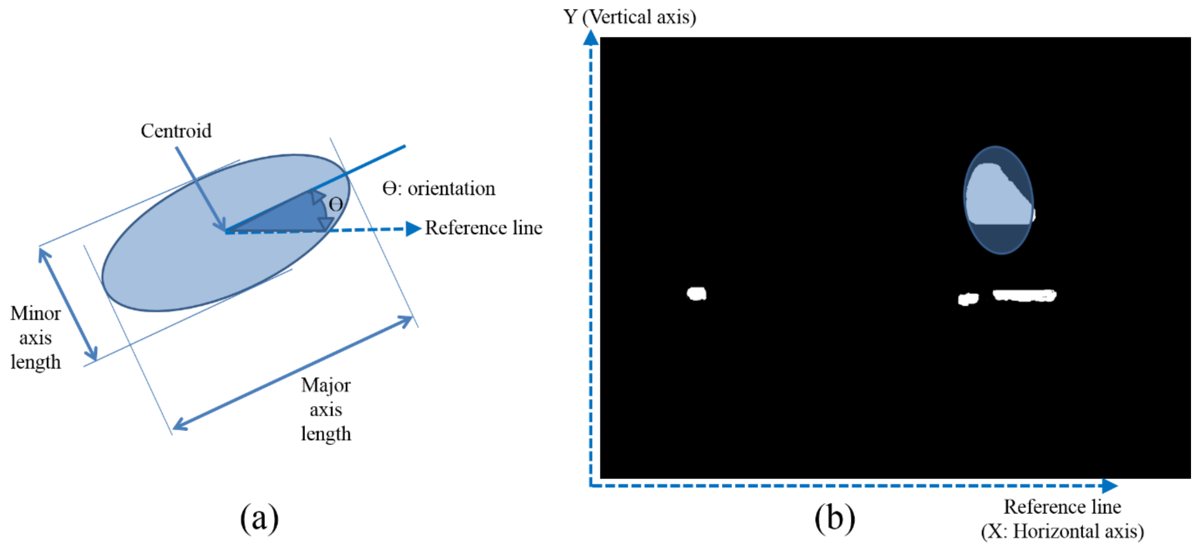

Figure 4-4. a. Ellipse parameters; b. Ellipse fitted to the partial hen body from figure 4-3c

4.2.4.1 Ellipse fitting

Since hens in the image are similar to an elliptical shape, an ellipse fitting algorithm was implemented to approximate every hen in order to separate or locate them.

Fitting an ellipse to a general conic can be accomplished by minimizing the algebraic distance over the set of N data points in a least-squares sense. Subsequently, the solution of the minimisation problem represents the best-fit ellipse for the given set of points. Each time, six edge sample points were randomly selected from the ordered edge points list for one ellipse fitting. The result of finding fitted ellipses is shown in figure 4-4b. Mathematical details of the ellipse fitting algorithm have been documented by Fitzgibbon et al. (1999).

Thereafter, ellipse parameters such as “Orientation”, “Major Axis Length”, “Minor Axis Length” and “Centroid” for all objects in the image were calculated. Figure 4-4a illustrates these parameters and figure 4-4b shows the ellipse fitted to the hen body that could be detected in a compartment using this method. The other smaller blobs in the figure were ignored since their size was below thresholds.

4.2.5 Hen choice test data collection

A choice-test study with individuals was conducted in which four hens (90 weeks of age) were each subjected to a 4-day choice test. Video was collected 24-h per day during this 16-day period and was used: (1) for comparing the performance of the automated analysis system to manual assessment of occupancy, and (2) for an initial assessment of aversion to ammoniated atmospheric conditions.

The ammonia concentration was controlled independently in each compartment with a feedback control system, and distinct concentrations were attained within a few ppm_v of the set point. Vertical hanging acrylic doors separated each compartment, which improved the control of ammonia at distinct levels, and hens were trained to open them in a separate training apparatus prior to introduction to the preference chamber. Details of the chamber construction, control system, and ammonia control performance are documented in (Sales et al., 2013).

4.2.6 Comparing the IPS to Human Video Observations

Video segments were manually labelled for comparison with IPS analysis. The hen's position within the EPC was tracked by the IPS for half an hour per day (15 min in the morning and 15 min in the afternoon) over 16 days while the hen navigated through compartments. EPC test videos were analysed every second for hen location by researchers and graduate students at the Animal Welfare and Environmental Sciences Laboratory at the University of Illinois. Preliminary observations allowed for the selection of distributed sessions throughout the experiment to compare automated to manually labelled occupancy. These sessions were not selected according to a fixed time of the day since videos had been captured on an event-basis. The behaviour of each individual hen was labelled using Jet-audio Player software (Cowon International) and by instantaneous logging of the occupied compartment in Microsoft Excel. As explained in section 4.2.3, 36000 scan samples were obtained and used for algorithm development. For each scan sample, occupancy of a compartment was monitored and logged. Occupancy behaviour was defined as the appearance of 20% of the topview body area of an average hen, which was equal to 14000 pixels for the physical arrangement in which the experiments carried out. Average area error of this method is 2.5 cm^2. If no hen was present in a compartment or less than the object area mentioned above was detected, that compartment was considered to be empty.

Every second of occupancy detection resulted from the IPS was compared with the same second result achieved from Human Video Observations. Here summary of statistics were compared instead of a statistical comparison. True Positive (TP) rate and False Positive (FP) rate was calculated for each day and False Negative (FN) could be calculated as 100-TP (Storey, 2003).

4.2.7 Validating choice-test positioning data: Ammonia aversion study

After developing the IPS technology explained above, the whole data set, namely 460800 frames, was analysed to investigate ammonia aversion behaviour. Each four-day choice test consisted of three different phases of data collection: acclimation (one day), baseline (one day) and treatment (two days).

During the acclimation phase, the hen had time to adapt to the environment in the EPC and learn to navigate between compartments. During the subsequent baseline phase, no ammonia concentration was applied. This functioned as the reference for the treatment phase. In the treatment phase, ammonia concentration of 0, 10, 20 or 40 ppm_v was randomly assigned to each compartment (table 4-1). During these periods, the video of each compartment was captured and occupancy by the hen was assessed using the IPS. As shown in the table, the experiment was carried out in four replications. In each replication, setup and timing was kept identical while different ammonia concentrations were randomly applied to different compartments during treatment phases. This helped to cancel the effect of compartment choice for a certain level of ammonia.

Data were summarised per replication. In each replication, acclimation (one day), baseline (one day) and treatment (two days) phases motion events, captured by the Geovision system were merged to make a single video file. The time budget of occupancy for each compartment was tallied and a total occupancy percentage was calculated for each compartment per day. If a hen was not documented in any compartment, it was assigned to be in a passageway between two compartments. No assessment of which tunnel was included in this analysis, though it could be added in the future with a logic sequence. Subsequently, statistical summary of occupancy percentages was compared among the compartments for each day and phase. Finally, a correlation between occupancy in compartments per phase and applied ammonia concentration on the same phase was sought. All compartments were designed and kept in identical situations, thus no compartment effect was included in the assessment and correlations between occupancy and compartment were not calculated.

Table 4-1. Ammonia (NH_3) concentration in different compartments during 16 days of the experiment. Each hen represents a replicate of the experiment

Replication	Stage	Days	NH_3 concentration in NW Compartment (ppm_v[1])	NH_3 concentration in NE Compartment (ppm_v)	NH_3 concentration in SW Compartment (ppm_v)	NH_3 concentration in SE Compartment (ppm_v)
1	Acclimation 1	1	0	0	0	0
	Baseline 1	2	0	0	0	0
	Treatment 1	3, 4	40	20	10	0
2	Acclimation 2	5	0	0	0	0
	Baseline 2	6	0	0	0	0
	Treatment 2	7, 8	0	10	20	40
3	Acclimation 3	9	0	0	0	0
	Baseline 3	10	0	0	0	0
	Treatment 3	11, 12	10	40	0	20
4	Acclimation 4	13	0	0	0	0
	Baseline 4	14	0	0	0	0
	Treatment 4	15, 16	0	40	10	20

4.3 Results and discussion

4.3.1 Hen Location Tracking

Figure 4-5 depicts a hen's movement within the EPC including jumps (misdetections) for one day. At time labels Ev_1, Ev_2, Ev_3 and Ev_4, the chart shows a jump from the NE to the SW compartment and vice versa, which is an impossible occurrence since these are opposite compartments and therefore not interconnected (figure 4-3a). It was verified with video that the hen moved quickly from NE to SW, being undetected in the NW compartment. Although misdetections were scattered during bird tracking, their causes could be further assessed and minimised for future studies. Some ideas to improve IPS detection within the EPC include installing the camera at an increased height

[1] Part Per Million by Volume

and using colour camera. The former will provide a broader camera field of view, and the latter will help to improve image segmentation.

4.3.2 Algorithm Development

The IPS registered 95.9 ± 2.6% of the actual occupancy during trials and 4.2% ± 3.0% false occupancy was reported by the IPS. The distribution of detection rates over the 16-days analysed was summarised in Figure 5, which was generally uniform from day to day. Figure 4-6 compares the IPS success rate with Human Video Observations as reference.

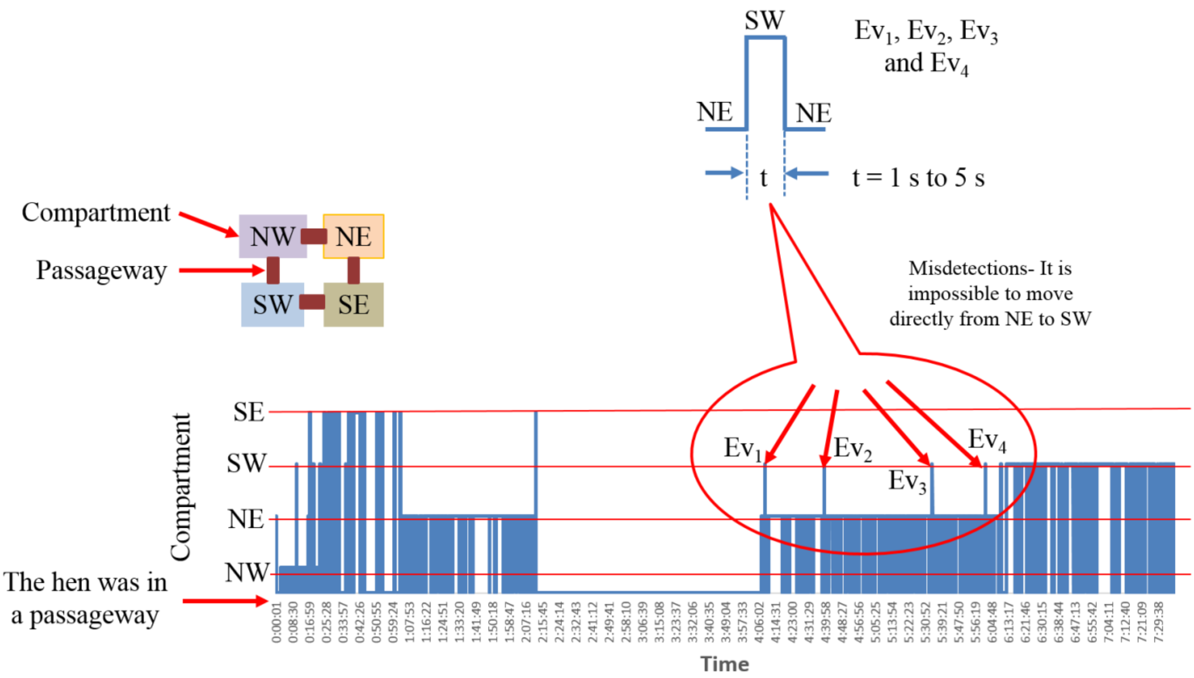

Figure 4-5. IPS detection of a hen navigating the EPC. Misdetection demonstrates that the IPS failed to detect a hen passing through a compartment in less than one second. For example for events Ev_1 to Ev_4 the hen could only go from NE to SW compartment through either SE or NW compartment, but no hen was detected in the latter compartments. This was because the hen transited through SE compartment quickly (<1 s).

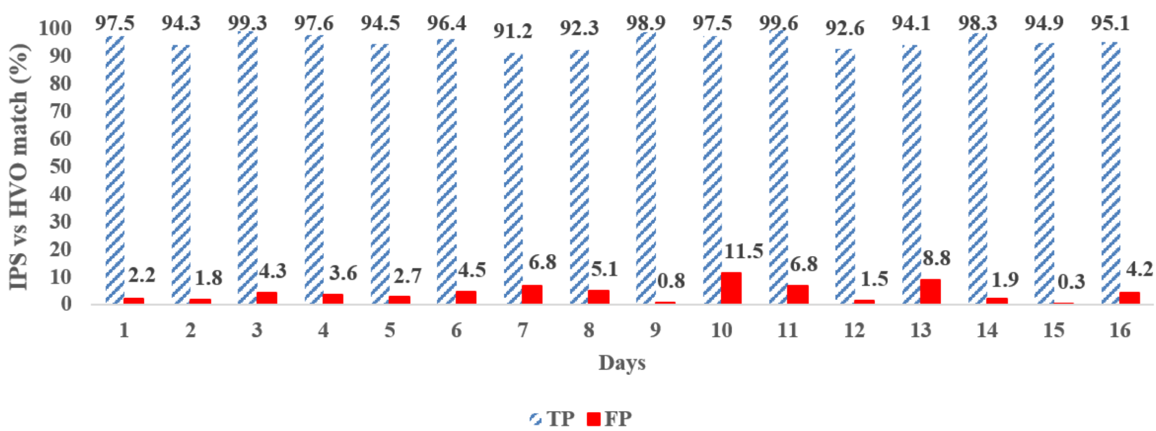

Figure 4-6. IPS vs. Human Video Observations match

These detection success rates showed that automated video monitoring is suitable for precisely monitoring occupancy of compartments in the EPC. Misdetections were observed, as shown in figure 4-6, and were related to 1) the inaccurate segmentations, which were due to variable illumination and similarity of the background to the hen's topview image; 2) the hen moving faster than the IPS could detect. Higher data quality, e.g. colour or three-Dimensional (3D) image, might provide a more robust detection system.

4.3.3 Continuous video analysis for ammonia aversion analysis

Table 4-2 shows average occupancy of each compartment in percentage for each period and figure 4-7 illustrates this parameter for the whole experiment.

For most of acclimation and baseline stages, hens picked a specific "home" compartment, meaning that they spent most of their time in one compartment (table 4-2). The "home" compartment was not the same compartment among the four hens tested. Based on results presented in table 4-2 and figure 4-7, occupancy was lower for compartments with 40 ppm_v of ammonia concentration while it was higher for 20 ppm_v compared with lower levels. Moreover, correlation of occupancy with ammonia for data points shown in table 4-2 was -16.47 per cent (not significant at alpha = 0.05). Although this correlation is insignificant, it demonstrates that hens tended to avoid compartments with a higher (more than 20 ppm_v) level of ammonia. Additional replications are needed to form a stronger conclusion regarding hen behavioural responses to ammonia in a choice test.

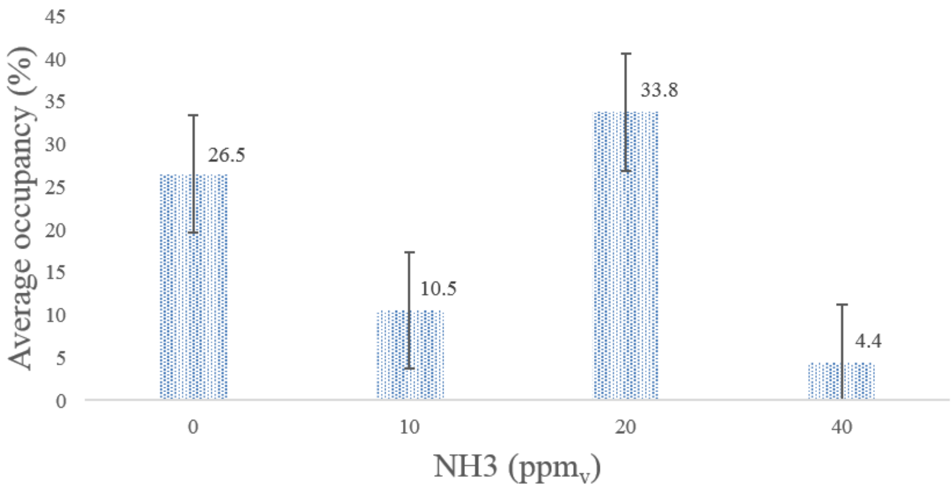

Figure 4-7. Average occupancy of the compartments vs. NH3 concentration in the EPC;

Table 4-2. NH_3 concentration (in ppm_v) vs. occupancy (in percentage) of four EPC compartments during 16 days of the experiment. Occupancy in passageways summarises the time when the hens were not detected in the quad compartments. Each hen represents a replicate of the experiment.

Replication	Stage	Day	NW Comp.[1]		NE Comp.		SW Comp.		SE Comp.		Passageways
			NH_3 (ppm_v[2])	Occ.[3] (%)	NH_3 (ppm_v)	Occ. (%)	NH_3 (ppm_v)	Occ. (%)	NH_3 (ppm_v)	Occ. (%)	Occ. (%)
1	Acclimation 1	1	0	4	0	15	0	6	0	3	72
	Baseline 1	2	0	0	0	0	0	43	0	32	25
	Treatment 1.1	3	40	0	20	0	10	11	0	71	18
	Treatment 1.2	4	40	0	20	0	10	0	0	86	14
2	Acclimation 2	5	0	0	0	0	0	74	0	21	5
	Baseline 2	6	0	0	0	11	0	88	0	0	12
	Treatment 2.1	7	0	85	10	0	20	1	40	6	8
	Treatment 2.2	8	0	0	10	0	20	99	40	0	1
3	Acclimation 3	9	0	98	0	0	0	0	0	0	2
	Baseline 3	10	0	80	0	5	0	0	0	15	0
	Treatment 3.1	11	10	73	40	0	0	25	20	2	0
	Treatment 3.2	12	10	0	40	0	0	97	20	0	3
4	Acclimation 4	13	0	99	0	0	0	0	0	0	1
	Baseline 4	14	0	1	0	5	0	1	0	93	0
	Treatment 4.1	15	0	1	40	3	10	0	20	96	0
	Treatment 4.2	16	0	2	40	26	10	0	20	72	0

This initial application of the IPS for assessing occupancy during a choice test demonstrates the successful implementation of an automated system for image analysis for occupancy.

Overall, the IPS performed well in a stainless-steel enclosure containing a hen with cameras installed above the compartments. Each camera covered the entire test bird area of a compartment. This system functioned to track hen navigation through detection of a hen navigating the compartments. To identify potential image processing misdetections and their causes, results of automated tracking were compared to Human Video Observations. During a choice-test study, mean ± Standard Deviation (SD) success detection rates were 95.9 ± 2.6% for an individual bird when measuring compartment occupancy. Sources of misdetection included i) Hens in adjacent compartments were visible in camera view and misled the segmentation and ellipse fitting algorithms; ii) Similarity of hen's feather colour to background and variable illumination; and iii) Fast transition of the hen between compartments.

To validate choice-test positioning data in an application, the IPS introduced in this work was subsequently employed to monitor laying hen ammonia aversion. The initial hypothesis was that hens tended to prefer a compartment with lower ammonia level and avoid those with higher levels. Results obtained in this work revealed a trend for aversion of ammonia levels of 40 ppm_v,

[1] Compartment

[2] Part Per Million by Volume

[3] Occupancy

but no aversion for 20 ppm_v or below. Differences observed were not significant, and additional examination including additional replications should be completed to strengthen the analysis.

Considering above results, one might think what advantages of the IPS are. Firstly, the IPS significantly reduces costs and data processing time compared to the expensive and time-intensive alternative of manual video analysis. Visual observation for a multiple choice behaviour would cost about 50 to 90 dollars for each hour of data and it could take about three times the length of the experiment to be carried out. In comparison, assuming usage of the IPS for three experiments and a development period of six months, this would cost 10 dollars for each hour of data and would take one fifth the length of the experiment. This is five to nine times cheaper and 15 times faster than visual observations. Secondly, scoring is affected by expectations of the observer and his bias could influence subjective scores of animal behaviour and welfare (Tuyttens et al., 2014). Thus, lack of the intra-observer repeatability is also an issue in labelling (Van Hertem et al., 2014) which does not exist in automatic monitoring.

In conclusion, the IPS system is suitable for determining the total time hens spend in each EPC compartment and related behaviours such as ammonia aversion. In general, this technology is suitable for choice tests where a topview camera is of use. For future studies, using colour or 3D cameras and painting hens for identification may contribute to improving IPS performance in the EPC. In addition, since monitoring the animals' preferences is one of many functions of the camera used in our design, this algorithm has to be fast enough to be integrated into the monitoring system. Otherwise our monitoring application will not be able to run in real-time. Processing time of all the algorithms developed in this PhD is discussed in section 8.2.1.

Chapter 5 Automatic Weight Estimation of Individual Pigs Using Image Analysis

Article title: Automatic Weight Estimation of Individual Pigs Using Image Analysis

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In chapter 4 image processing was employed to monitor laying hen ammonia aversion. The initial hypothesis was that hens tend to prefer a compartment with lower ammonia levels and avoid those with higher levels. This is important since it is known from literature that ammonia could have a negative effect on animal performance (Deaton et al., 1982).

Being able to automatically monitor and interpret how and why animals move, is the basis for understanding how this affects the performance. Important indicators of animal performance are weight gain, drinking behaviour and feeding behaviour.

Individual weight measurement is the most important variable in meat focused production systems. However, utilizing manual scales for this purpose is labour intensive and requires movement of animals, which can be stressful for both the animals and workers. Machine vision-based weighing of animals is a non-intrusive, fast and accurate approach, avoiding stress for both the animal and the farmer and producing weight data every day of a fattening cycle (Wang et al., 2008). This technology uses aerial-view images of animals provided by cameras to determine body surface dimensions and may be used for real-time monitoring of pig weight. Since weight gain, as a biological response to feed intake, varies among animals in a pen, it is important to monitor weight for each animal individually. This helps the farmer to check on slow-growing animals and to make appropriate management changes and to ensure animals deliver a satisfactory performance. Animal's performance (topview body area or weight) could be affected by its zone preference (e.g. the feeding zone) in its living area as illustrated in figure 5-1. This evolves from the idea of zone preference investigated in the previous chapter (please see figure 4-1). In this case, when an animal visits its feeder more frequently and gives longer visits to the feeder, it is expected to grow more rapidly than when its visits are less frequent and shorter.

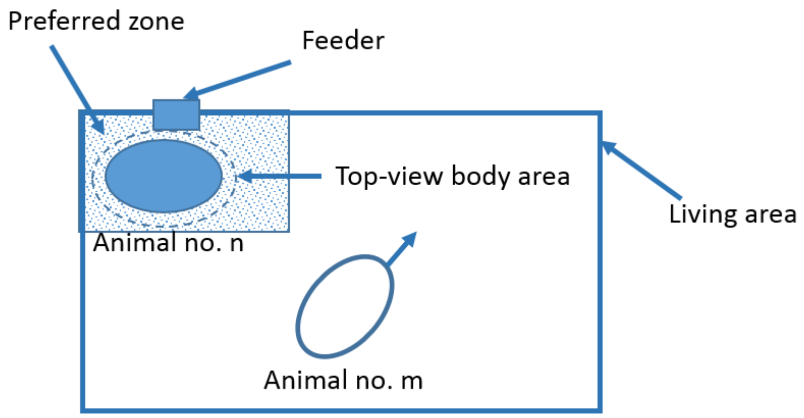


Figure 5-1. Schematic: performance (topview body area or weight) of animals could be affected by their zone preferences

5.1 Introduction

Technologies are presently available that can monitor individual animals automatically 24 h a day. Research reported by (DeShazer et al., 1988) identified over 90 potential applications for image analysis in pig production. Of these, estimation of pig weight was identified as a primary application for the development of image analysis techniques for use in livestock production. Accurate monitoring of weight gain performance and the use of weight data to make effective management decisions is also crucial for efficient pork production. As farms continue to grow in size, even small alterations to production practices can have a large impact on overall profit in grow-finish pig operations (De Lange and Dewey, 2006). Knowledge of daily weight gain would allow producers to optimise nutritional management practices, predict and control shipping weights, and potentially assist in monitoring herd health (Schofield et al., 1999).

The main aim of PLF is to continuously collect relevant information about key aspects of livestock production in order to ensure that an optimal production process can be achieved. This is done to maximise production efficiency and profitability while minimizing the potentially negative environmental, animal welfare and human health impacts of the livestock production processes (Banhazi et al., 2007; Banhazi and Black, 2009). It is obvious that one of the key aspects of animal production is the weight of the animals. Therefore, it should be monitored frequently.

Individual weight measurement is an important variable in farm management that nonetheless suffers from a number of drawbacks when performed manually. Firstly, utilizing manual scales is labour intensive and requires movement of animals, which can be stressful for both animals and workers. Secondly, mechanical equipment is prone to malfunction as a result of exposure to dirt, dust, moisture and direct contact with animals. Gathering performance data using a manual scale is therefore done sparingly, generally only at the beginning and end of a production period and most often only for a representative subset of animals, and not for every animal (Schofield, 1990). Machine vision-based weighing of pigs is a non-intrusive, fast and accurate approach, which could reduce stress for both the animal and the farmer during the weighing process (Wang et al., 2008). Since slow weight gain can happen for some of the pigs in a pen, it is important to monitor weight for each pig individually. This helps the farmer to check slow-growing pigs and to make appropriate management changes.

Recently, VIA has been proposed as a method for real-time and continuous monitoring of pig weight gain performance, thereby allowing quicker detection of problems and more effective management decisions (Marchant et al., 1999). The VIA technique uses aerial-view images of animals provided by cameras to determine body surface dimensions and may be used for real-time monitoring of pig weight. Since video analysis of pigs has numerous other applications (Van der Stuyft et al., 1991; Xin, 1999; Kollis et al., 2007) weight estimation using videos can be an added value for farmers provided they utilise vision technology.

The concepts of relating size and shape to weight are not new to the field of animal science. According to Whittemore and Schofield (2000), Hammond and Brody were already exploring these concepts in the 1930s and 1940s, with Brody making connections between surface area and live body weight (BW). Historically, consideration of size and shape for evaluation of weight was rejected in favour of direct measurement of live BW due to the difficulty in obtaining the required measurements (Whittemore and Schofield, 2000). Paddy Schofield did, as a main researcher in this field, start a company to bring this solution to farmers by offering them a camera based system for daily weight measurement. Moving from the comfort zone of science to the competitive commercial market showed that developing a good solution in practice is a hard step to make. The solution so far requires animals to be in a standardised position. To capture this position and calculate measures the animal must be isolated in the image. Due to changing light conditions many images are not useful or calculations are not accurate enough. This requires manual control of images and calculated values to become reliable results with a useful degree of accuracy. More recently however, these concepts have been revisited, as advances in technology make it possible to obtain the required size and shape measurements under current pork production practices.

One of the most important contribution in past research was the finding that the area of the topview of the pig, minus the head and neck is most strongly correlated to BW (Schofield, 1990). Variation in other components has little effect on estimated live BW, and can therefore be inferred based on the size of the animal's body. Camera technology can be used to determine the area of the aerial view of a pig's body. Using information on the relationship between area and BW, VIA systems have been developed and have been found to be accurate enough to estimate live BW within 5% (Schofield, 1990), but to date, this technology has required that pigs were separated from a group for analysis as an individual.

Other researchers previously investigated different approaches to estimate weight of pigs using image analysis. Brandl and Jørgensen (1996) used spline functions to express the relationship between the body area of the pig measured by image analysis and the live weight of the pig. Marchant et al. (1999) developed automated algorithms that could find the plan view outline of pigs in a normal housing situation, measure major body components and predict the weight of the group of pigs at 34 kg with standard errors of 7.3% while using manual weighing to calibrate the system. Schofield et al. (1999) developed prototype imaging systems to record the weight-related areas of pigs by fitting linear regression coefficients. Furthermore, they could log the growth rates of three groups of pigs of three genetic strains to within 5%. Whittemore and Schofield (2000) examined the value of the estimation of size and shape for animal description in relation to nutrient use in breeding sows and growing pigs. Craig and Schinkel (2001) proposed a mixed effects model[1] to estimate pig weight. White et al. (2004) used a VIA system to continuously collect size and shape data of a total of 116 pigs from 25 to 115 kg of weight for three types of pigs and could classify these groups in 64 to 83% of observations. Wang et al. (2008) developed an image-based walk-through system for pig live weight approximation. They employed an artificial neural network technique to correlate physical features extracted from the walk-

[1] Mixed-effects models, like many other types of statistical models, describe a relationship between a response variable and the covariates that have been measured or observed along with the response. For further information please see (Pinheiro and Bates, 2000)

through images to pig live weight in order to improve the accuracy of live weight approximation and could estimate pig weight with an average relative error of 3%.

Some suggest that BW and topview body area have a linear relationship (Marchant et al., 1999; Schofield et al., 1999; White et al., 2004) and use a single linear regression equation to estimate the live BW of animals from the body area based on the interpretation of individual images. Schofield et al. (1999) suggested that different breeds may require different algorithms for BW prediction. Also Fisher et al. (2003) and Green et al. (2003) suggested a need for unique algorithms for specific breeds or lines of pigs. More recently, researchers have been highlighting the benefits of mixed effects models (Schinkel et al., 2009) and justify their argument that mixed effects model is easily adaptable to stochastic modelling. However, despite the advantages of mixed effects models compared to fixed effects models, it is important to note that there is a large amount of variation in the accuracy of different mixed effects models.

In this work, dynamic data based (or Transfer Function: TF) models were used. Such modelling techniques are compact and allow accurate prediction of the time-variant process response, which makes them suitable for model-based predictive monitoring purposes (Aerts et al., 2003b).

In this chapter, an approach is analysed to monitor pig weights in a fully automated way based on continuous image analysis. The hypothesis in this work is that combining TF modelling and topview pig body area calculation using image processing could lead to a more accurate weight estimation.

5.2 Materials and Methods

5.2.1 Animals and housing

Two experiments, identical in setup, were carried out in February and June 2011, whereby data from the former were used to develop the model while the latter was a validation experiment. Experiments were previously explained in section 2.2.1.

5.2.2 Equipment and data collection

Pig body weight was also measured twice a week using MS Schippers MS-100 weighing scale. These measurements served as the gold standard reference to which the estimated weights obtained from image analysis and modelling were compared.

The rest of equipment and data collection process were identical to section 2.2.2.

5.2.3 Localising and segmenting pigs image by ellipse fitting

First, pig image was segmented using the process explained in section 2.2.3. Second, the corpus image was separated from the head by using the same ellipse fitting algorithm. Here, the algorithm gave two ellipses as shown in figure 5-2a. The larger ellipse represents the corpus and the smaller one the head. The corpus area of the pig surrounded by the corpus ellipse, namely “A” in figure 5-2b was calculated once a min and used for BW estimation. In order to limit processing to standard standing positions of pigs in weight estimation, 2700 area pixels (for camera height of 2.2 m) were regarded as a minimum of "A".

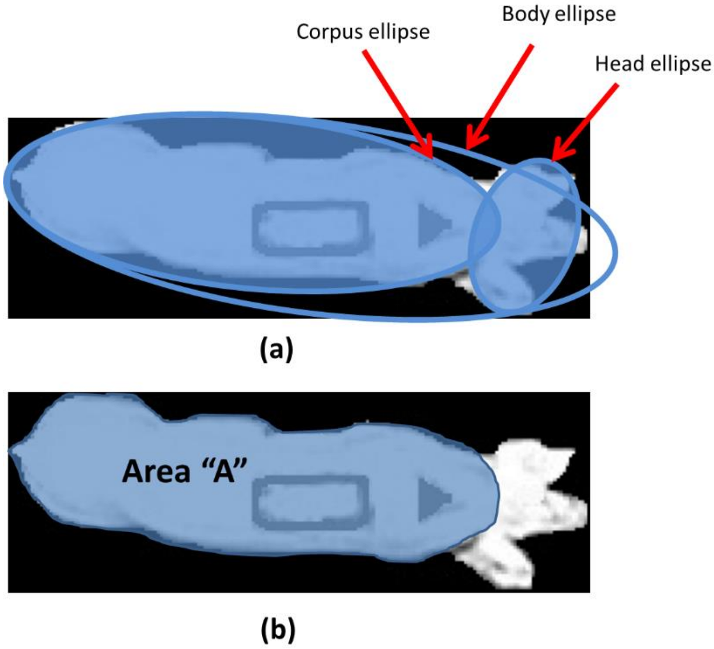


Figure 5-2. a. Extracted pig body using ellipse fitting; corpus and head separation by repeating ellipse fitting algorithm; b. The resulting body area "A" used for BW estimation.

5.2.4 Identification of pigs

Since the aim was to estimate individual pig weight as well as at group level, pigs needed to be marked for identification. The identification process was explained in section 2.2.3.

5.2.5 Weight estimation using the TF model

The objective of the next step was to quantify the dynamics of body area (A) and to relate it to the gold standard BW. A single-input, single-output (SISO) TF model was used. The model structure used could be described by equation 5.1 (Young, 2011).

$$BW(td) = \frac{a(Z^{-1})}{b(Z^{-1})} A(t - n_T td) \qquad (5.1)$$

In the above equation BW(td) is the body weight, td represents the discrete-time increments for weight estimation and measurement; A(td) represents the input of the model, namely Body Area; $n_i td$ is the number of time delays between each input i and their first effects on the output; $a(z^{-1})$ is the numerator polynomial and equals $1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_{n_a} z^{-n_a}$; $b_i(z^{-1})$ is the denumerator polynomial linked with the inputs i and is equal to $b_{0i} + b_{1i} z^{-1} + b_{2i} z^{-2} + \cdots + b_{n_{bi}} z^{-n_{bi}}$; a_j , b_i are the model parameters to be estimated; z^{-1} is the backward shift operator, defined as $z^{-1}.y(k) = y(k-1)$; n_a, n_b are the orders of the respective polynomials.

The model parameters were estimated using a refined instrumental variable approach with the Captain toolbox in Matlab (Young, 2011). In order to build the model, different combinations for n_a, n_b and n_T were calculated. More specifically, in the SISO model which has only one input, n_a ranged from 1 to 3, n_b from 1 up to 3 and n_T from 0 to 2. Therefore, to identify the best fitting TF model parameters of a total of 48 (4x4x3) possible models were calculated. The resulting models were evaluated by the coefficient of determination R^2 (Young and Lees, 1993) and an identification procedure was used to select the most appropriate model order based on the minimisation of the Young Identification Criterion (YIC) explained by Young and Lees (1993). The smaller the variance of the model residuals in relation to the variance of the measured output, the more negative this term becomes.

Weight measurements in the first and development experiment were used to design the model. The developed model was then used to estimate the BW in the second and validation experiment, which was methodologically identical.

Finally, results of TF modelling were compared against a linear regression model (Schofield et al., 1999) and a non-linear mixed effects model (Schinkel et al., 2009).

5.3 Results

Using the methods adopted in this chapter, pigs were identified and their topview body area was measured automatically. As a reference, every pig was manually weighed two times a week.

When applying the modelling approach to the data of the whole experiment (240 measurements) the YIC criterion selected models which were predominantly second order (equation 5.2) and without delay, stable (namely all of the poles within the unit circle) and with the highest R^2. The optimal model structure was described by n_a=2, n_b = 1 and n_T= 0 (equation 5.2) based on parameters demonstrated in equation 5.1.

$$BW(t) = \frac{b_1.z^{-1}}{1+a_1.z^{-1}+a_2.z^{-2}} A(t) \qquad (5.2)$$

The specific values for the model parameters (a_1, a_2 and b_1) are presented in table 5-1. The model described the weight measurement for 240 measurements with R_t^2 of 97.5%. As seen in the table, YIC is optimally low and the standard deviation of the a-parameters and b-parameter is low as well.

Table 5-1. Specification of the TF model developed using BW measurement as the output and body area as input

YIC	R^2	Parameter estimate
-7.294	0.975	a_1 = -0.0768 (0.0061)* a_2 = 0.9609 (0.0093)* b_1 = 0.289 (0.0014)*

* The parameter estimates are accompanied by associated standard deviations in parenthesis.

Figure 5-3 illustrates the adapted model with the optimal parameters shown in above table.

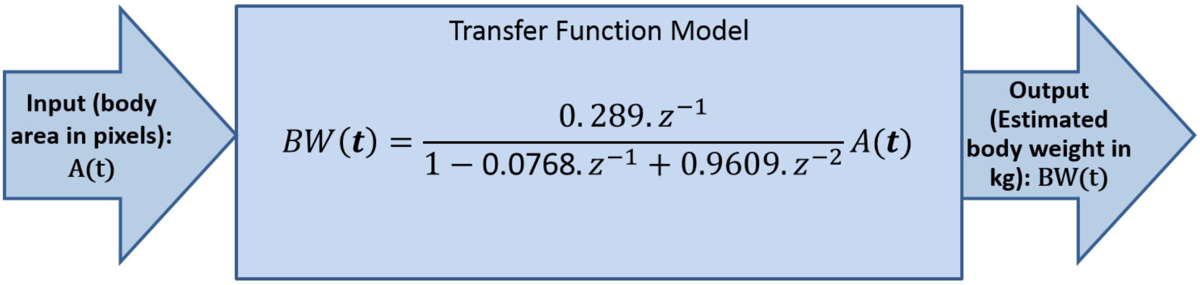


Figure 5-3. The TF model adapted to estimate BW (in kg) using body area (in pixels) as input.

Figure 5-4 compares weight estimation results calculated by the model (using average daily body area) shown in figure 5-3 with actual weight measurements on those days for pen 1 in the validation experiment. Figure 5-5 shows the measured actual weights versus the estimated weights over six days of measurements for all four pens and ten pigs per pen (240 data points). The ideal case was that all of the data points align with the identity line (R^2 of 100% which means for every data point, estimated weight would equal the measured weight). This means the more erratic the points are, the lower R^2 and accuracy of weight estimation will be.

In total, using TF modelling of topview pig body area, pigs weight could be estimated with an accuracy of 97.5% and 96.2% at group[1] and individual level, respectively.

[1] Group level weight estimation is derived from calculating an average of individuals' weight

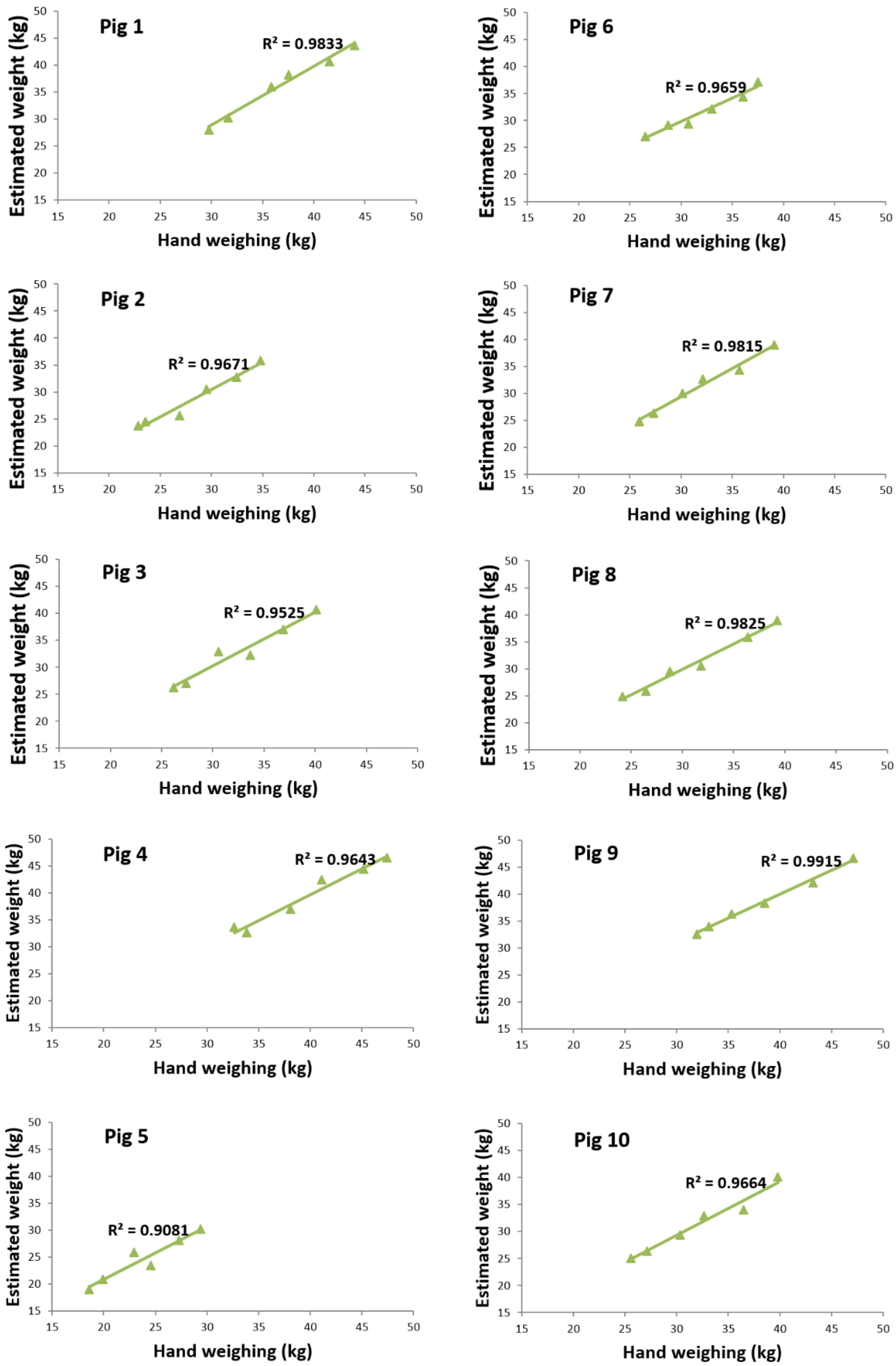


Figure 5-4. Weight estimation versus measurements for each pig in pen 1 on six measurement days during the experiment. The average R^2 for weight estimation for this pen was 0.9663.

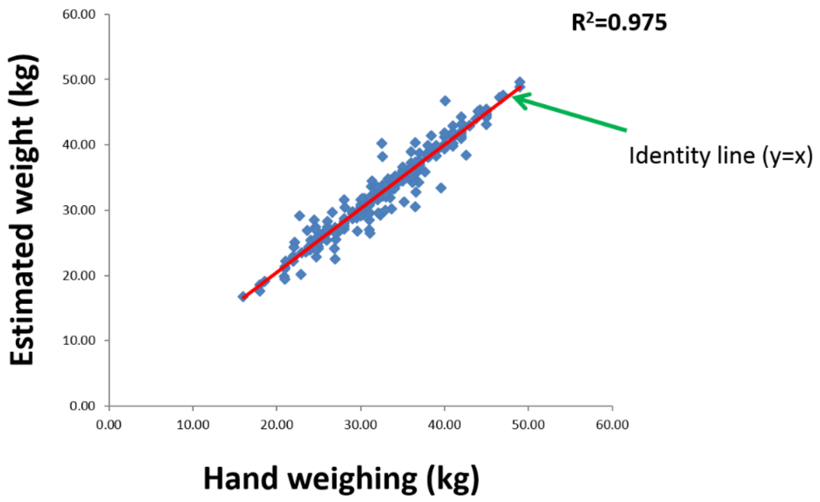


Figure 5-5. Measured weights versus estimated weights over six measurement days of all four pens with ten pigs per pen (240 data points) in the validation experiment. Overall R^2 is 0.975 with standard error of 0.0182.

5.4 Discussion

The proposed image processing and modelling method proved the ability to work unattended in an environment with the pigs increasing in weight from a mean of 23 to 45 kg. The system calculated an average of one area measurement every one min. Subsequently, the body area calculated by the image processing was used to design a TF model with weight measurements as output. The resulting model was evaluated in a validation experiment in which the body area was the input of the model. The model output, namely the estimated weight, was subsequently compared against conventional weight measurements. This displayed a R^2 of 0.9663 for pen 1 at individual animal level. Average weight of individuals in a group (group level) was also estimated using the developed model. Taking all four pens into account R^2 was as high as 0.975 for group weight estimation and 0.962 for individual pig weight estimation. These results prove that the mean weight of the individual pigs can be estimated with a deviation of 2.5% in a weight range of 23 to 45 kg.

The results obtained using TF model were compared with previous work on this topic, namely linear regression models (Schofield et al., 1999) and mixed effects (non-linear) models (Schinkel et al., 2009). Table 5-2 compares the results of these three methods applied to the group level data of the validation experiment while data of the first experiment were used to develop the models.

The data presented in table 5-2 indicate that the TF model yields a higher R^2 and a lower SD, which means this method can estimate BW with a higher accuracy and reliability. In addition, the proposed method is capable of estimating BW for individual pigs with an accuracy of 96.2% (SD= 1.23 kg) while the competing methods do not support automatic individual pig weight estimation.

Table 5-2. Comparison of results of applying "Linear regression", "Mixed effects (non-linear)" and TF models to body area data in group level

Model	Data points	R^2	SD[1] (%)	SD (kg)
Linear regression	240	0.871	10.04	4.52
Mixed effects (non-linear)	240	0.943	5.95	2.68
TF	240	0.975	1.82	0.82

In terms of practical application of this method, problems should be solved as a number of pitfalls have been identified for this study. The first problem is related to individual identification of pigs using a dye marker. The problem arising from faded colour patterns and pigs being dirty will need to be addressed if they are to be reliably monitored using image analysis techniques under actual farm conditions. That is, poor results may be caused by dirt on a pig resulting in poor definition of the body edge and area by the measurement algorithm. Another problem lays in the application of paint pattern as such. On the one hand, dirt on the pig or fading paint patterns can cause a low identification rate. On the other hand, application of paint patterns are questionable in terms of convenience for the farmer. These problems need to be considered in the further development of the image illumination and capturing techniques, as well as in the software development for image processing.

A second pitfall is when certain pigs stood on their back feet and therefore presented a reduced area for image capturing and analysis. These cases were automatically excluded by thresholding the minimum body area.

A third pitfall was in illumination conditions, which are also important for identification and segmentation of the images. On the one hand, overly bright illumination could prevent accurate identification since contrast of the dark paint patterns on a bright pig skin could decrease. On the other hand, however, a dim illumination could make pig segmentation against dark backgrounds more difficult. In the experiments of this work, it was found that a range of light intensity of 40 to 150 lux would be optimal.

The final pitfall was the frequent calibration this method needed for updating model parameters. If these parameters are not updated every few days, prediction weights might deviate from measured ones. This is because transfer function model cannot be adaptive enough to cope with image boundary variations for weight prediction over a long period of time.

At the time of conducting this research work, the solution proposed was the cheapest and the best for algorithm development since cameras were used for many other applications as well (Kashiha et al., 2013a). For future work, however, a more practical identification method such as electronic tags might be considered. Alternatively, algorithms may be developed for identification of animals deviating from the mean of desired growth without the need for individual tagging. In addition, since weight gain over time is supposed to be closely related to health and behaviours such as feeding in pigs

[1] Standard Deviation

(Hessel et al., 2006), growth patterns and correlation of weight gain with behaviours will be investigated. Finally, since monitoring weight estimation is one of many functions of the camera used in our design, this algorithm has to be fast enough to be integrated into the monitoring system. Otherwise our monitoring application will not be able to run in real-time. Processing time of all the algorithms developed in this PhD is discussed in section 8.2.1.

5.5 Conclusion

A technique has been found that offers fully automated weight estimation of pigs. By marking pigs, it became possible to estimate their weight individually using topview video processing. The results show that by measuring the topview body area and adapting a TF model, it is possible to estimate BW with an accuracy of 97.5% (SD = 0.82 kg) on group level and 96.2% (SD = 1.23 kg) on individual level overcoming competing linear and non-linear modelling methods. In conclusion, application of the introduced method can bring significant profits for livestock enterprises since continuous information on daily weight would allow producers to optimise nutritional management practices, predict and control shipping weights, and potentially assist in monitoring and improving herd health.

Chapter 6 Can a Camera Measure the Water Volume Usage of Pigs?

Article title: The Automatic Monitoring of Pigs Water Use by Cameras

***Authors**: M. Kashiha, C. Bahr, S. Amirpour Haredasht, S. Ott, C. Moons, T. Niewold, F. Ödberg, D. Berckmans*

***Source**: Computers and Electronics in Agriculture, Vol. 90, pp. 164-169*

Drinking behaviour and water volume usage are important indicators of satisfactory performance, health and other parameters in animal husbandry. For example, feed and water volume usage are closely related and solid feed intake must be accompanied by water intake. Monitoring of the drinking behaviour of pigs could be useful in detection of diseases and other production related problems too (Madsen and Kristensen, 2005b). Chapter 6 discusses development of an automated monitor tool for water volume usage by pigs in a pen. Animal's performance (here water volume usage) could be affected by its zone preference in its living area as illustrated in figure 6-1. This evolves from the idea of zone preference investigated in chapter 4 (please see figure 4-1).

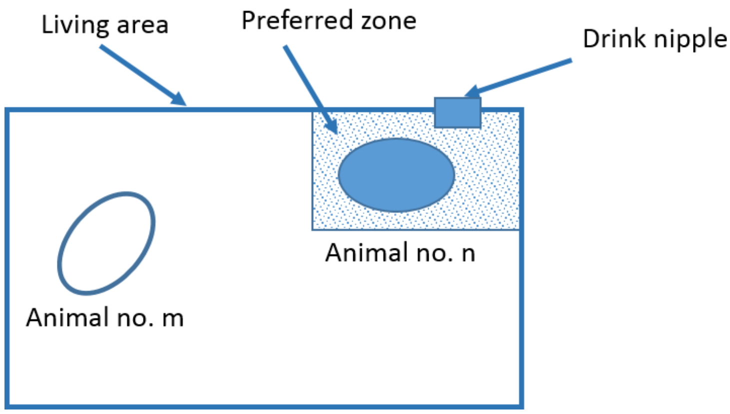


Figure 6-1. Schematic: performance (water volume usage) of animals could be affected by their zone preferences

6.1 Introduction

Technology makes it possible for producers to increase the number of animals in their flock or herd. While these systems allow a more efficient labour, the reduced ratio of farmers to animals results in welfare problems (HSUS, 2010). One of the essential components of welfare in animal husbandry is providing adequate food and water (Botreau et al., 2007). On the other hand, a substantial amount of man-hour is required to guarantee animals having efficient access to water and food. To meet the demands of the market while providing enough care to all animals, farmers might use automatic tools to monitor welfare and health of their animals.

Water is an essential need for pigs and inadequate access to it may result in reduced feed intake, reduced production and increased health problems (Gonyou, 1996). In addition, feed and water volume usage are closely related. The low level of eating may relate to insufficient drinking activity, as solid feed intake must be accompanied by water intake (Dybkjaer et al., 2006). Monitoring of the drinking behaviour of young pigs, has proved to be a useful tool in detection of diseases and other production related problems too. For instance, it is known that by on-line monitoring of water consumption of young pigs, an outbreak of diarrhoea can be detected approximately one day before physical signs are seen on the pigs (Madsen and Kristensen, 2005b) and the stops in the automatic feeders can be detected since these cause huge deviations in the level of water consumption (Madsen and Kristensen, 2005b). Therefore, it is beneficial to develop an automated monitor of water volume usage by pigs in a pen.

The idea of employing automatic image processing in livestock welfare monitoring is not new (Tillett, 1991; Van der Stuyft et al., 1991). Several studies have been carried out on comparing manual labelling of visits and water meter measurements (Madsen and Kristensen, 2005b; Meiszberg et al., 2009). However, automatic monitoring of visits to estimate water volume usage in a pig barn has never been reported in literature. The objective of this chapter is to analyse whether it is possible to estimate the continuous water volume usage of animals from a simple video camera above a pen with 10 fattening pigs.

This technique helps to improve pigs' welfare since problems in having access to water or abnormal drinking behaviours in pigs can be reported before it harms their health. Moreover, since automatic image processing facilitates combining drinking behaviour analysis with analysing other behaviours like feed intake, it is more advantageous in comparison with conventional water meters.

6.2 Materials and methods

6.2.1 Animals and housing

This section is identical to section 2.2.1.

6.2.2 Data collection

Using Noldus MPEG Recorder software, images were recorded during 13 days (upon the schedule demonstrated in table 6-1) in 3 weeks for 12 h per day, between 7.00 h and 19.00 h, resulting in 156 h of video. Equipment used were the same explained in section 2.2.2.

Table 6-1. Recording days of the experiment; on some of the days, recording had been stopped due to physiological measurements. Discussing these measurements is out of the scope of this study.

Week 1				Week 2					Week 3			
Day 1	Day 3	Day 4	Day 6	Day 8	Day 10	Day 11	Day 13	Day 14	Day 15	Day 17	Day 18	Day 20

6.2.3 Image segmentation

The first step to process was to segment the image in order to find the location of the pigs. The segmentation process was explained in section 2.2.3.

In order to find if a pig put his head at the drink nipple or not, it was necessary to identify the head (or ears) of the pigs. This was achieved by analysing the pig's body contour (Chaki and Parekh, 2012) in the segmented image. Figure 6-2a shows the pig's body with important points marked on it. Centroid of the pig's body image was taken as the reference in analysing his body contour profile. It was calculated using the equations 6.1 and 6.2. In equation 6.1, m_{pq} is the (p^{th} ,q^{th}) order torque of image function f(i,j) of the image I. In equation 6.2, X and Y of the centroid are calculated using the torque calculated in equation 6.1.

$$m_{pq} = \sum_{(i,j)\in I} i^p \times j^q \times f(i,j) \qquad (6.1)$$

$$X_{centroid} = \frac{m_{10}}{m_{00}}, Y_{centroid} = \frac{m_{01}}{m_{00}} \qquad (6.2)$$

By calculating the distance of the pig's body contour pixels from the centroid of his body, a distance profile shown in figure 6-2b was achieved. Points 3 and 5 relate to the ears of the animals. So, by finding minima and maxima of this plot, it was possible to detect ears and consequently the head of the animal.

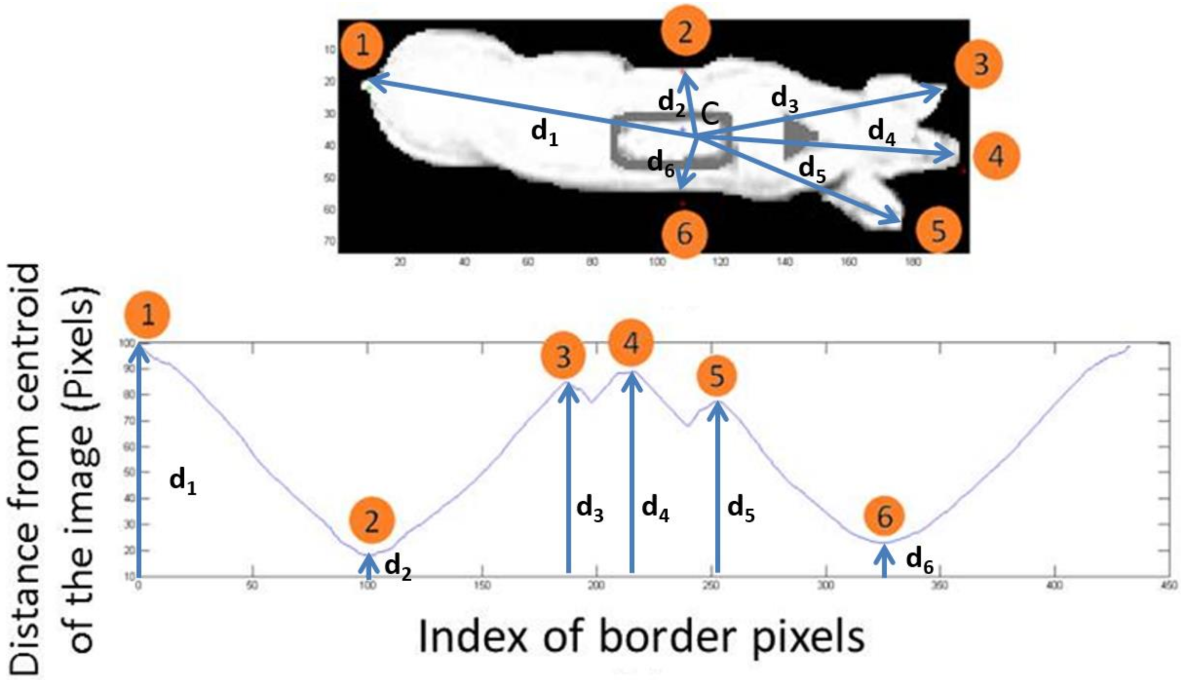


Figure 6-2. a. Important points of a pig's body contour; C is the centroid and d_i is the distance of the centroid to the point i, i=1, 2, ..., 6; b. Distance of pixels on body's contour from the centroid of body

6.2.3.1 Detection of drink nipple visits

Visually, the posture and position of pigs while being at the drink nipple is characteristic and easy to recognise. The criteria established for the drink nipple visit algorithm was that the pig had to stand still in the area adjacent the drink nipple and keep its snout in the water outlet for at least two seconds. Consequently, duration of the visit was registered. By definition, a visit is reported if either of the points 3, 4 or 5 (shown in figure 6-2) inside an ellipse is detected closer than 10 pixels to the drink nipple. Since the water outlet used in our experiments was directional, pigs could only drink if they stood in a certain position in the region shown in figure 6-3 and, as a result, only one pig at a time could drink (Magowan et al., 2007).

6.2.4 Water volume usage estimation using dynamic data-based modelling

Final goal of this work was to estimate half-hourly water volume usage in a pig barn by analysing half-hourly duration of drink nipple visits. To achieve that purpose, a data-based dynamic (or Transfer Function: TF) model was developed to quantify the dynamics of water meter measurements and to relate it with half-hourly duration of visits. Therefore, the main objective of the model was to estimate water volume usage in a pen by only analysing pen image automatically.

Figure 6-3. Possible drinking region for pigs at the drink nipple

First, a single-input, single-output (SISO) system was used to model the water volume usage as function of half-hourly duration of visits. The model structure used could be described as follows.

$$w(td) = \frac{a(z^{-1})}{b(z^{-1})} d(t - n_T \mathrm{td}) \tag{6.3}$$

where w(td) is the half-hourly water measurement; td represents discrete-time instants with a measurement interval of thirty min; d(td) represents the "half-hourly duration of visit" as the input of the model. n_T is the number of the time delays between each input i and their first effects on the output; $a(z^{-1})$ is the numerator polynomial and equals $1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_{n_a} z^{-n_a}$; $b(z^{-1})$ is the denominator polynomials linked with the inputs *i* and are equal to $b_{0i} + b_{1i} z^{-1} + b_{2i} z^{-2} + \cdots + b_{n_{bi}} z^{-n_{bi}}$; a_j , b_i are the model parameters to be estimated; z^{-1} is the backward shift operator, defined as $z^{-1}.y(k) = y(k-1)$; n_a, n_b are the orders of the respective polynomials.

This model was identical to the one explained in section 5.2.5. The model parameters were estimated using a refined instrumental variable approach with the Captain toolbox in MATLAB (Young, 2011). In order to build the model, different combinations for n_a, n_b and n_T were calculated. More specifically for the SISO model which has only one input, n_a ranged from 1 to 2, n_b from 1 up to 2 and n_T from 0 to 2. Therefore, to identify the first SISO model in total 12 (2x2x3) possible TF models were calculated.

6.3 Results

The aim of this study was to quantify the dynamics of the water volume usage in a pig barn and to relate it to the time pigs spent on drinking. Figure 6-4 a, b and c compare hourly duration of drink nipple visits of pigs with water meter measurements of pen 3 for 3 days of the experiment and table 6-2 presents the results of evaluating the model for the whole experiment (13 days). As observed in these graphs, water volume usage followed the trend of the half-hourly duration of visits.

When applying the modelling approach to the data of the whole experiment (13 days and 24 h a day) the YIC criterion selected models that were predominantly first order (equation 6.4), stable (namely all of the poles within the unit circle) and with highest R^2. The optimal model structure was described by $n_a=1$, $n_b = 1$ and $n_T= 0$ as demonstrated in equation 6.3.

$$w(t) = \frac{b_1.z^{-1}}{1+a_1.z^{-1}} d(t) \tag{6.4}$$

Table 6-2. R^2 between the hourly duration of visits to the drink nipple vs. water meter measurements in 13 days of the experiment; total average R^2 is 0.92; on some of the days, recording had been stopped due to physiological measurements. Discussing these measurements is out of the scope of this study.

Day	Pen 1	Pen 2	Pen 3	Pen 4
1	0.93	0.92	0.94	0.87
3	0.92	0.90	0.94	0.90
4	0.97	0.92	0.95	0.94
6	0.89	0.92	0.95	0.92
8	0.90	0.97	0.90	0.94
10	0.93	0.91	0.90	0.94
11	0.92	0.94	0.94	0.96
13	0.92	0.93	0.90	0.88
14	0.91	0.90	0.96	0.90
15	0.88	0.90	0.89	0.90
17	0.95	0.91	0.89	0.88
18	0.96	0.96	0.97	0.95
20	0.90	0.87	0.90	0.91
Total	0.92	0.92	0.93	0.91

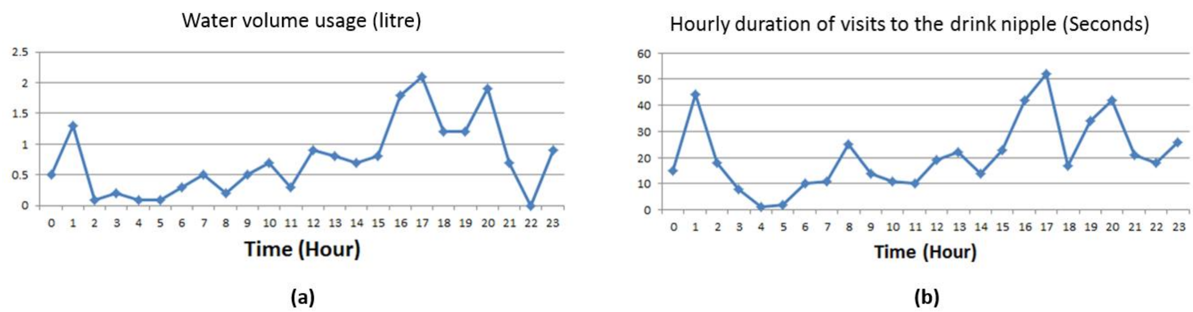


Figure 6-4. Hourly duration of visits in pen 3 to the drink nipple vs. water meter measurements a. Experiment day 1 (R^2= 0.94); b. Experiment day 8 (R^2= 0.90) ; c. Experiment day 15 (R^2= 0.89)

Result of using the applied transfer function model to estimate water volume usage is shown in figure 6-5 for the first day of the experiment. Quantitative results over 3 weeks of the experiment were similar to the values shown in figure 6-5.

The specific values for the model parameters (a_1 and b_1) are presented in table 6-3. The model described the half-hourly measured water volume usage over the 13 days with R^2 of 92% (average error of 220 millilitre). As seen in the table, YIC is optimally low and the standard deviation of the a-parameter and b-parameter is trivial.

Table 6-3. Specification of the dynamic linear model developed using water volume usage measurement as the output and half-hourly duration of visits to the drink nipple as input

YIC	R^2	Parameter estimate
-5.811	0.92	a_1 = -0.0768 (0.0153)* b_1= 0.0374 (0.0005.9)

* The parameter estimates are accompanied by associated standard deviations in parenthesis. The basis for computation of the standard deviation is each half-hourly computation.

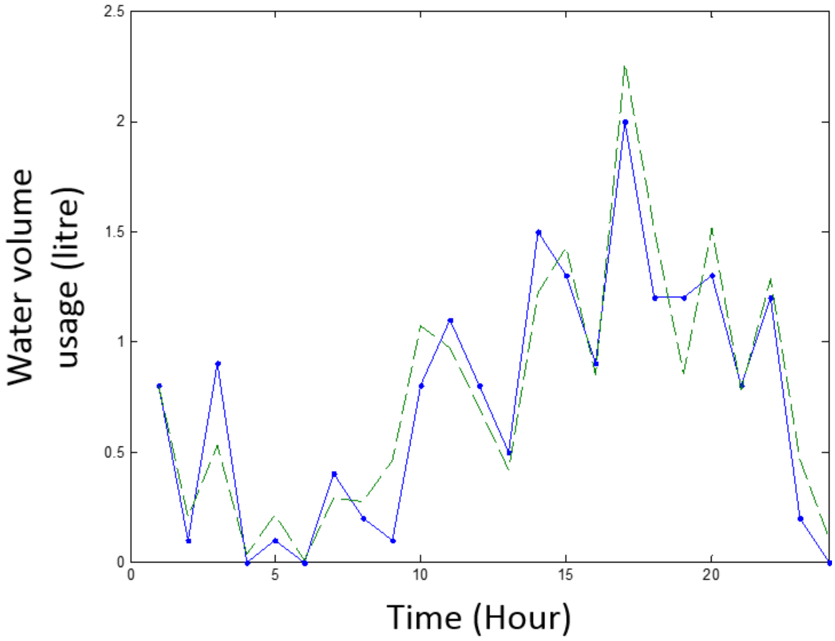


Figure 6-5. The resulting model (– –) of the data-based SISO model versus measured (—●—) water volume usage in 24 h (first day of the experiment)

6.4 Discussion

Automatic detection of animal behaviour has proved useful to farm managers. One application is monitoring of drinking which is a key behaviour in pigs and relates to many other welfare indexes. In normal situations pigs show a stable diurnal drinking pattern (Madsen et al., 2005a), whereas outbreak of diseases, changes in the quality of feed or ventilation problems often make the pigs' drinking behaviour deviate from the normal pattern. The existence of a drinking pattern and the specificity of drinking behaviour are criteria that allow using drinking behaviour as a predictor for health or production problems (Meiszberg et al., 2009). The findings of the study reported in (Musial et al., 1999) indicate that water intake for the pig follows a drinking pattern. This pattern is affected by different factors such as drinker design (Brumm et al., 2000), diet (Shaw et al., 2006), weight and size of pigs (Frederick et al., 2006), etc. Thus, analysing this pattern can yield useful information on suitability of pigs welfare.

Adopting automatic video processing is a popular technology in pigs welfare monitoring (DeShazer et al., 1988; Tillett et al., 1997; Lind et al., 2005). In this work, an innovative approach was chosen to estimate fattening pigs' water volume usage by automatic vision technology. Using image processing techniques, duration a pig stays at the drink nipple was calculated. To improve the accuracy of the applied algorithms, using image contour analysis methods, important parts of pigs' body, namely ears, head and head, were detected. This helped to find if a pigs stood in a standard drinking position. Comparing applying of this method with labelling of the drink nipple visits proved the method to be accurate.

Real time monitoring of growing pigs' water consumption seems to be a possible way of improving management (Bird and Crabtree, 2000). In order to be able to detect changes in drinking behaviour, it is crucial to have a well-founded model to predict the expected behaviour. In this work, a model was developed to relate duration of visits to the water volume usage. Developing a transfer function model in MATLAB Captain Toolbox resulted in several stable models with various delay, a-parameter and b-parameters. The simplest model was a first-order model without a delay. Adapting this model to those two parameters, one as input (duration of visits) and the other as output (water volume usage) resulted in R^2 of 92% (average error of 220 millilitre). Therefore, it can be concluded that by monitoring drink nipple visits in a pen, one can accurately estimate amount of water pigs use. The significance of this work lies in its ability to automatise drinking behaviour of pigs which is but one of many behaviours that can be monitored automatically using video processing techniques.

6.5 Conclusion

In this work, a surprising result was obtained when investigating the opportunities of estimating water volume usage of fattening pigs automatically by vision technology. Estimating water volume usage of pigs can help us to understand how drinking behaviour of pigs is related to their water volume usage. As such, this method offers many potential applications to improve animal husbandry management.

The analysis described above indicates that it is possible to perform real-time camera vision-based water volume usage estimation in a pig pen. This analysis may contribute to improve automatic analysis of drinking behaviour based on topview video processing. The results showed that by automatic image processing and transfer function modelling, half-hourly water volume usage could be estimated with high accuracy. The presented approach is able to estimate the half-hourly water volume usage of pigs in a barn with an accuracy of 92% (average error of 220 millilitre) in reference to the gold standard, namely water meter. Finally, since monitoring the water volume usage is one of many functions of the camera used in our design, this algorithm has to be fast enough to be integrated into the real-time monitoring system. Processing time of all the algorithms developed in this PhD is discussed in section 8.2.1.

Chapter 7 Development of an Early Warning System For a Broiler House Using Computer Vision

***Article title**:* Development of an Early Warning System For a Broiler House Using Computer Vision

***Authors**: M. Kashiha, A. Pluk, C. Bahr, E. Vranken, D. Berckmans*

***Source**: Biosystems Engineering, Vol. 116, issue 1, pp. 36-45*

In chapter 5, animal weight estimation of pigs using VIA was presented. This method relies on a single camera as a sensor installed above a pig pen to estimate animal's weight through topview body area measurement and dynamic modelling. The biggest advantage of the method is that no labour input is needed and animals will not be bothered nor stressed during the measurement.

In chapter 6, monitoring drinking behaviour was discussed. Drinking is a key behaviour in pigs and relates to many other welfare indexes. The existence of a drinking pattern and the specificity of drinking behaviour are criteria that allow using drinking behaviour as a predictor for health or production problems (Meiszberg et al., 2009). The findings of the study reported in (Musial et al., 1999) indicate that water intake for the pig follows a drinking pattern. This pattern is affected by different factors such as drinker design (Brumm et al., 2000), diet (Shaw et al., 2006), weight and size of pigs (Frederick et al., 2006), etc. Thus, analysing this pattern can yield useful information on suitability of pigs' welfare.

Movement of animals within their living area and preferring certain zones not only affects their individual performance (such as water volume usage and weight gain), but also their group performance and behaviour. In production systems most animals are kept in groups. Because of the size of these groups it is still difficult to monitor performance, health and welfare on individual level. Therefore, it is worthwhile to investigate if we can, with a few simple measures, make a link between group behaviour and animal health, welfare and performance.

It is clear that many variables can cause less than optimal results in these complex processes, such as animals growing in large groups. There are environmental controls with variables such as temperature, humidity, gas concentration and air velocity. Access to feed and water in a group with the social interactions is another factor. All these can fail and cause problems. The basic idea of this chapter was to analyse whether simple variables of animal group behaviour that are calculated continuously might help to detect problems.

Welfare monitoring using image analysis could be performed both at individual and group level. Weight gain and drinking behaviour mentioned above are two of the welfare indicators that could be monitored both individually and in a group. However, there are behaviours that are only meaningful at group level. For instance, distribution of animals within a pen is calculated at group level. This chapter discusses how measuring and prediction of animal distribution could help to improve animal welfare.

Figure 7-1 shows a schematic of a group of animals whose performance and behaviour could be affected by their group preference in their living area. This evolves from the idea of individual animal preferences investigated in previous chapters.

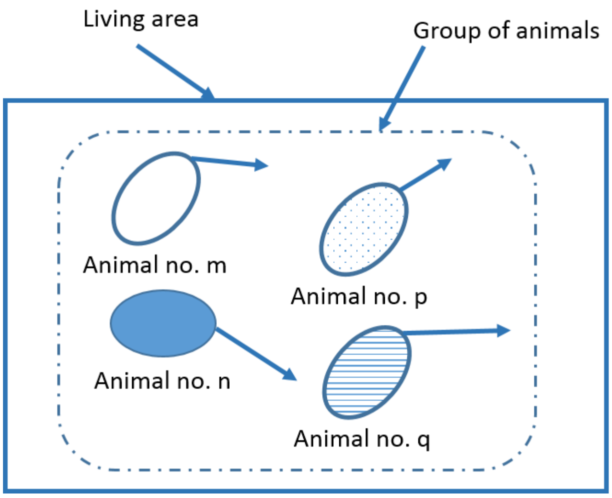


Figure 7-1. Schematic: performance and behaviour of animals could be affected by their group preferences

7.1 Introduction

According to FAO[1] (Cluff and Jones, 2010), this decade the annual world poultry production is expected to increase by 2.8%. During the same period, the total broiler meat production will jump from 96.9 to 124.1 million tons, exceeding growth in all other meat production sectors (Penz Junior and Goncalves Bruno, 2011). Farmers, on the other hand, achieve very low margins per individual animal. Therefore, intensive broiler-keeping is unavoidable and management in broiler houses is crucial. Modern farmers are confronted with increasing pressure to care for a large number of animals per farm, which will become even more acute in future years. Good care is the key for high levels of productivity, health and welfare, and thus for an economically viable business. State-of-the-art technical support can bring the farmer closer to the animals by assisting him in gathering information about his animals and presenting it in a workable format. The use of technology in livestock production is the core idea of PLF (Lokhorst and Koerkamp, 2009; Wrest Park History, 2009). More specifically, such technology offers a high potential for monitoring of livestock in real time (Lokhorst and Koerkamp, 2009). Continuous automated monitoring of the varying needs of individual living organisms has become a technologically feasible option which can be implemented anywhere needed. This technique facilitates the development of "early warning systems", which improve the response time to individual animals' needs. Accordingly, employing such a tool to monitor the broilers can help farmers substantially to manage their house more efficiently (EFSA, 2012).

Using cameras and automatic image processing, it is possible to collect information on the behaviour of broilers, analyse the data and detect possible deviations from expected values, This is also a highly cost-effective approach which significantly reduces the man-hours needed to regularly check a broiler house (Borgonovo, 2009).

Technology of monitoring broilers by image processing has already been practised by many scientific researchers. De Wet et al. (2003) employed computer-assisted image analysis to estimate daily body weight changes of broiler chickens. They could estimate the body weight of the broilers on average with a relative error of about 11% from image surface area. Aydin et al. (2010) applied an automatic tool to assess the activity of broiler chickens with different gait scores (ability to walk). Kristensen and Cornou (2011) investigated possibility of detecting leg disorders in broiler chickens through analysing deviations in activity level measured by image analysis. Dawkins et al. (2009) showed that automated measures of optical flow have the potential to provide continuous 'outcome' measures of the welfare state of the flock and are highly correlated with gait scores and so have the possibility to become a useful adjunct to the much more labour intensive process of gait scoring in broilers and Roberts et al. (2012) used optical flow technique to predict welfare outcome of broiler chickens 1-2 days in advance.

What is missing in previous works is an algorithm that can report all kind of problems of the poultry house in real-time and can help the farmer to manage keeping his broilers

[1]Food and Agriculture Organisation

more efficiently since they are currently facing many welfare problems in broiler houses due to intensive breeding of broilers (Duncan, 2001). This will also promote broiler welfare.

The hypothesis of this work is that several problems that will affect the animal performance can be noticed from the animal behaviour. It is assumed that the earliest sign of a problem can be found in the animal behaviour long before they change daily growth rate or feed conversion.

One of the indexes to monitor broiler welfare is distribution (EFSA, 2012). Sudden variations in distribution index could be linked to thermal discomfort, insufficient feeding or drinking and many other welfare issues (Febrer et al., 2006). Objective of this chapter was to find a method for early warning of general problems in a commercial house using measuring the distribution index of broilers and a real-time monitoring technique.

7.2 Materials and Methods

7.2.1 The eYeNamic system

The eYeNamic system is a useful image pre-processing tool used for livestock monitoring (Costa et al., 2009). This system is equipped with three identical Mobotix M24SEC22-D22 IP-cameras with real focal length of 4 mm, horizontal image angel of 90 degrees and vertical image angel of 67 degrees. Hardware in experiment of this work was consisted of a setup with 3 topview cameras installed in the ridge at the height of 5 meters and distributed over the length of the house which was 63.5 meters long to capture topview images over concrete floor with wood shavings. Each camera was in a protective cover to shield it from dust and moisture. Images were captured with a resolution of 1280 by 960 pixels and a 0.5 Hz frame rate in MPEG format. These cameras were connected to a PC over the farm network. Figure 7-2 shows how the input images looked like when three cameras were used. Top view images were used because this solution is simple and robust to implement in field conditions and produces the most useful data for the purpose of this study (Van der Stuyft et al., 1991).

Using Mx Control Centre (V2.4 MOBOTIX AG, Germany) software, images were recorded during broilers growth period (42 days) continuously and eYeNamic data were collected every 5 min. This resulted in 2880 h of videos (5184000 images).

Although one image was captured every two seconds, eYeNamic gave out its pre-processed data every 5 min. This data were an average of all the images during the mentioned period. The lens was pointed downwards to get a topview of the ground surface, but due to using wide angle lenses, image corners were distorted as observed in figure 7-2. This phenomenon is known as fish-eye effect (Hughes et al., 2008). To avoid such distortion, we used a correction algorithm as described in Altera (2008).

eYeNamic measures amount of object pixels in ratio to background with average absolute error of 8%. These pixel ratios are used for calculating distribution index. This calculation will be explained in section 7.2.3.

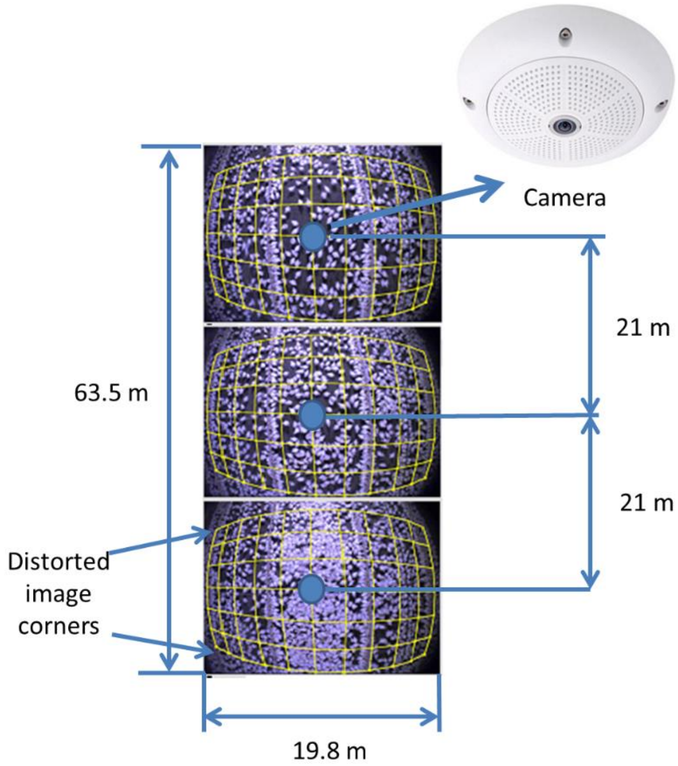


Figure 7-2. Picture of the ground surface in a broiler house equipped with eYeNamic devided to 60 1 by1 meter zones in one camera’s image.

7.2.2. Birds and housing

For the experiments, a commercial broiler house in the Netherlands was equipped with an eYeNamic system. In the application of this work eYeNamic allowed following the behaviour of the broilers flock from min to min. Clear topview images showed the distribution index of the animals and abnormal behaviour was visible immediately, enabling one to respond in time before it could affect the welfare or health of the animals. Abnormality was defined as a sudden drop in distribution (or escaping of a flock of broilers from a certain region in the house) that mainly could happen due to malfunctioning of feeders, drinkers, heating, ventilation or a visiting human. Mathematically this was interpreted as a sudden drop of more than 25% from expected distribution which was depending on growth rate.

During the experiment, video recordings of the broilers in the house were made continuously for 42 days (for the whole growth period). Images collected from the eYeNamic system together with time and date labels were exported to CSV (Comma Separated Values) files. These files were analysed in MATLAB subsequently.

This study comprised two experiments, each for 42 days. Experiments were carried out in a commercial broiler farm. The first experiment data were used for development and the second for validation. In each experiment, day old broilers with a weight of 40 ± 5 grams were brought to the house and grew up during 42 days. The key specifications of the experiment were as follows: The house had dimensions of 19.8 meters by 63.5 meters and a height of 5.10 m and housed 28000 Ross 308 broilers. It was equipped with a climate control system (type Fancom FUP1EA2) and Fancom[1] Minimum Transitional Tunnel (MTT) ventilation concept with Fancom ImagO-system (Mixed air ventilation). Water was freely available to all birds by means of 5 drinking lines during the light periods. Food was a combination of wheat and pellets (start, growth and finish) and an automatic feeding system (type Fancom FWBU2B1) was used. The feeding regime was based on the amounts shown in table 7-1.

Mean air temperature was set at 34°C during day 1 while temperature was decreased gradually until 20°C at the end of the growth period. Light was switched on and off four times a day, so there were 4 light periods with a minimum light intensity of 5 lux and a maximum of 10 lux (when the light was on) for 5 h and 4 dark periods (when the light was off). The start of the first light period was at 3.00 h. Figure 7-3 shows a topview image of the birds in the house in a surface of 19.8 by 63.5 m at the age of 27 days.

During the first monitoring period of 42 days (experiment 1) no logbook was produced by the farmer. The data of this experiment were used for developing the model used for prediction of the next light periods data. In the validation experiment, however, a logbook was filled in by the farmer indicating the events happening in the house. In other words, he wrote down any problem that he felt it could affect welfare and health of his broilers. This was taken as a reference to validate the algorithm. Figure 7-4 shows the process of data processing using eYeNamic monitor tool versus manual scoring of the events by farmer. The logbook and the validation process are explained in section 7.2.4.2.

Table 7-1. Feeding regime during a growth period

Bird age (d)	**1**	**4**	**8**	**10**	**14**	**17**	**28**	**42**
Feed regime (gram.animal^{-1})	0.012	0.022	0.034	0.043	0.064	0.080	0.136	0.195

Figure 7-3. Topview camera image of the commercial broiler house in the Netherlands (house area 19.8 m x 63.5 m)

[1] Fancom BV, Panningen, The Netherlands

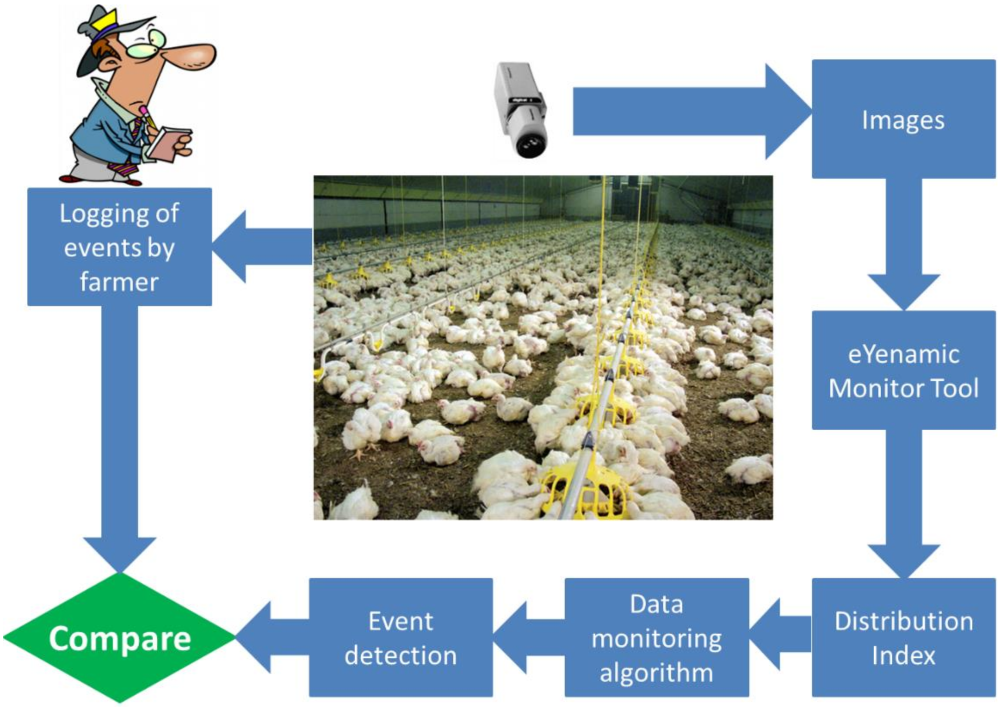


Figure 7-4. Data processing using the eYeNamic monitor tool versus the manual scoring of the events by farmer.

7.2.3 Distribution index calculation

To calculate the animal distribution index, the image captured by each camera was divided to 10 x 6 zones and the occupancy density of broilers in each zone was considered after binarising the image using histogram shape-based thresholding explained by Cherry and Barwick (1962) and Buyse et al. (1996).

Zone Occupancy Density (ZOD) in zone (i, j) was calculated using equation 7.1.

$$ZOD_{i,j}(t) = \frac{\sum_{(x,y)\in Z_{i,j}} O(x,y,t)}{Z_s(i,j)} * 100 \qquad (7.1)$$

In the above equation, O(x,y,t) is the occupancy (foreground pixels in the binary image) of zone x,y (grids in figure 7-2) at time t and Z_s is the size of the zone in pixels.

There were 60 zones per camera and 3 cameras in the house, so in total there were180 zones. For covering a total of 28000 birds, the average occupancy rate of all zones from the different cameras was calculated using equation 7.2.

$$\overline{ZOD(t)} = \frac{\sum_c^C \sum_i^M \sum_j^N ZOD_{i,j}(t)}{C \times M \times N} \qquad (7.2)$$

In the above equation, M and N are the number of rows and columns of zones respectively and C is the number of cameras. In the example shown in figure 7-5, this is the arithmetic mean of the 180 values from the three matrices along. The mean value here is 36 (per 1 m^2).

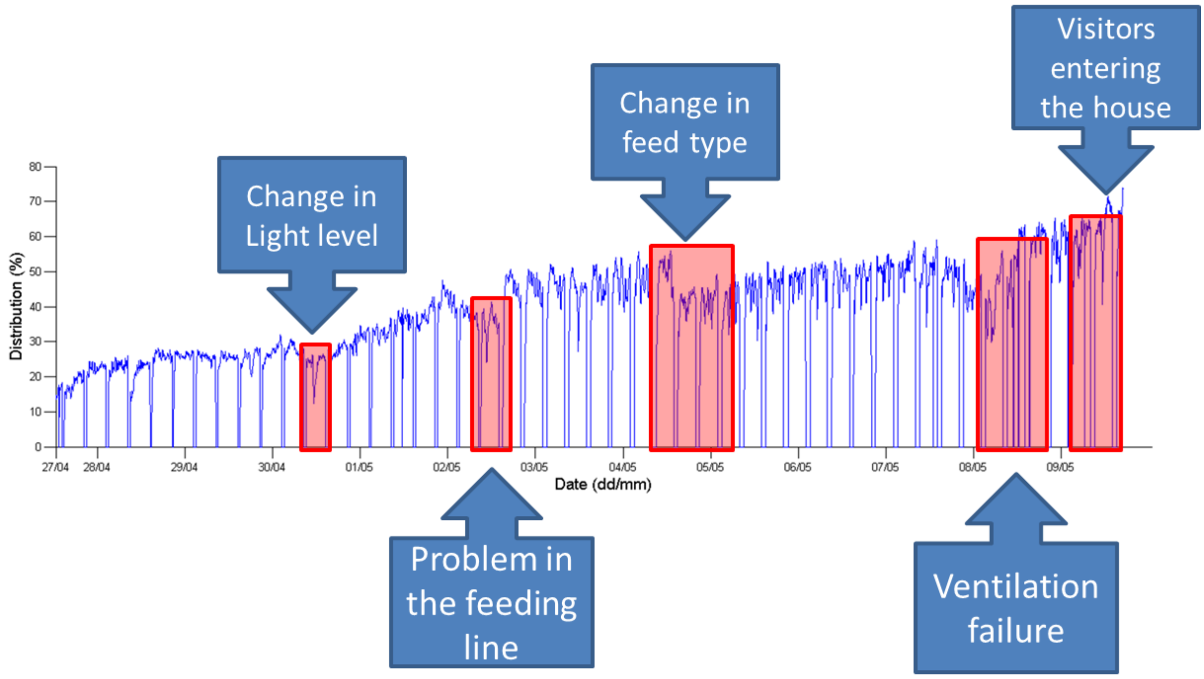


Figure 7-5. Occurrences in the broiler house that affect the distribution index. Some of these events are demonstrated in this figure such as “change in light level”, “change in feed type”, “ventilation failure” and “visitors entering the house”

Using ZOD(i,j)(t) of each of the cameras the distribution index is calculated from the three matrices. All values (180 in this example) are checked to see how many of them are out of the range of 20% from $\overline{\text{ZOD(t)}}$. Equation 7.3 shows how this calculation is performed (α is a threshold coefficient and equals 0.2 or 20%).

$$U_{i,j}(t) = \begin{cases} 1 & if \; |ZOD_{i,j}(t) - \overline{ZOD}(t)| < \alpha \times \overline{ZOD}(t) \\ 0 & else \end{cases} \qquad (7.3)$$

Where $U_{i,j}(t)$ is a zone occupancy binary value and the rest of variables are as defined previously.

Finally, the distribution index is yielded by equation 7.4 (α = 0.2).

$$UI(t) = \frac{\#Zones\ with\ |ZOD_{i,j}(t) - \overline{ZOD}(t)| < \alpha \times \overline{ZOD}(t)}{C \times M \times N} \qquad (7.4)$$

In the above example 67.2% of the numbers are recorded in the range of ±20% of the average (= 36). The distribution index is thus 67.2%.

7.2.4 The real-time monitoring algorithm

Although growth rate and distribution index of broilers follows a non-linear trend, these can be considered linear in short interval of several light periods (figure 7-10) (Rogers et al., 1987). This trend can be affected by several factors including problems in feeding or drinking system, light intensity, etc. as shown in figure 7-6, thus analysing the data can help to detect the events happening in the house. To detect these events, a model-based algorithm was developed.

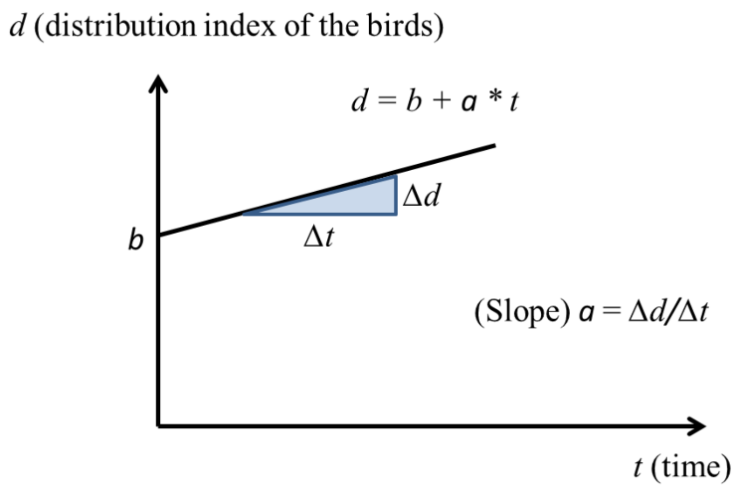
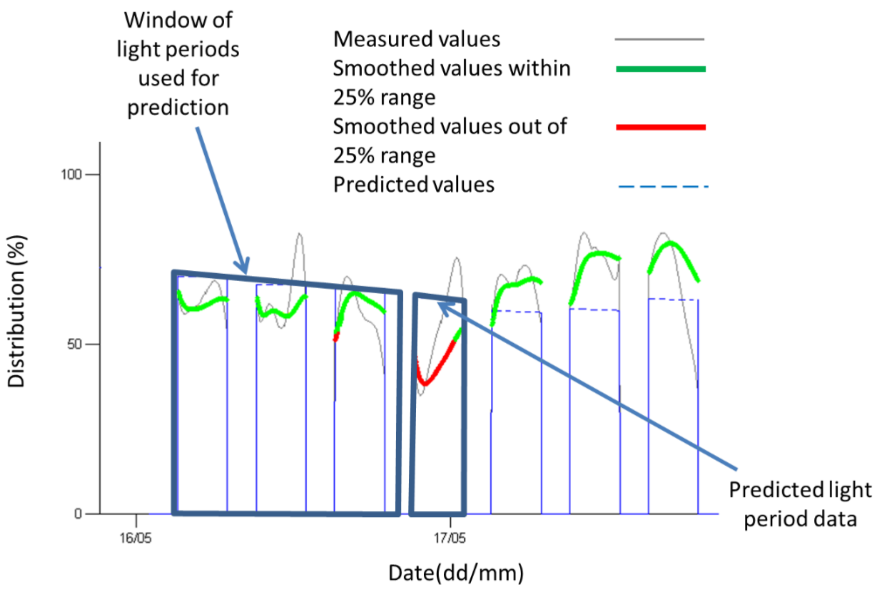


Figure 7-6. Linear real-time model used to predict distribution index; *b* is the final distribution index value in the previous light period; *a* (the predicted slope of the current light period) is the average slope of distribution index change in the last three light periods

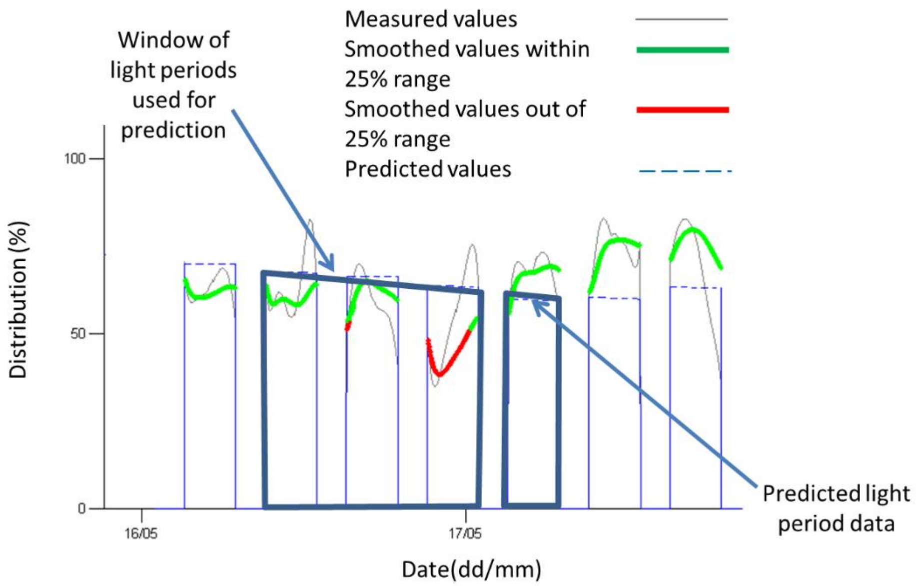
7.2.4.1 Development of the adaptive real-time model

As mentioned in the section 7.2.2, two identical experiments were carried out in this work. Based on the data of experiment 1, a linear real-time model (Pulido-Calvo et al., 2007) was developed and tested to model the distribution index of the birds as a response to the light input. Since distribution index varies linearly over time, this model is designed to predict the data of next light periods using the average slope of the previous periods. Benefits of such a model is that it is simple, fast and implementable for real-time applications and has the capability to adapt itself to variations in data.

Linear real-time refers to a model in which the conditional mean of Y given the value of X is an affine function of X (Tanaka and Watada, 1988). A real-time model can be used to fit a predictive model to an observed data set of Y and X values. If a new value of X is given without its accompanying value of Y, then the fitted model can be used to make a prediction of the value of Y. The least square approach has been used to fit the Y = a * X + b linear real-time model shown in figure 7-6. Mathematical details of this model can be found in (Draper and Smith, 1981). In figure 7-7, b is the final distribution index value of the previous light periods and K (the predicted slope of the current light period) is the average slope of distribution index change in the last three light periods. K and b were adapted for each light period and this process was repeated for each light period recursively. Using this model, an online prediction could be made on the distribution index each time the light was switched on.



(a)



(b)

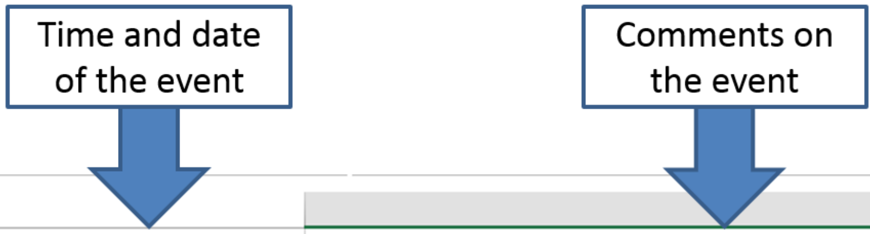
Figure 7-7. Prediction window (consisting of three light periods) shifts from (a) to (b) to predict the next light period data.

In case the measured values are deviating from the predicted standard values, an event might have happened in the house. As shown in figure 7-7a and b, the predicted values are categorised based on deviation from the measured values (thin grey line) as follows:
(1) thick bright grey line: less than 25% of negative or positive deviation from the measured values; this means the prediction is fulfilled. (2) thick dark grey line: more than 25% of negative or positive deviation from the measured values; this means the prediction has lost following the measured values. If the faulty (dark thick grey line) region continues for more than 15 min, an alarm will be generated.

The prediction model explained above works based on a moving window. The moving window is shifted for one light period each time and next light period data are predicted as shown in figure 7-7.

7.2.4.2 Validation of the model

In the second experiment a logbook was filled by the farmer. A piece of the logbook of the validation experiment is shown in figure 7-8. He filled in the logbook whenever he knew there was a problem, for instance with feeder lines, or when he was observing an abnormal behaviour of broilers. The events recorded by him were compared with the alarm regions (thick dark grey line in figure 7-7) generated by the algorithm. The results of the comparison will follow in the next section.



1		
2	Time	Comment
3	19-10-2011 18:53:44	A feeder was blocked
4	20-10-2011 11:30:17	Light problem, change of light scheme
5	27-10-2011 19:26-12	Our caretaker walked around the shed
6	28-10-2011 21:13:34	Problem with water flow adjustment
7	6-11-2011 11:13:30	Problem with feeder motor, some feeder lines remained empty for two hours
8	10-11-2011 6:55:14	Unloading part of the chickens to free space for the rest

Figure 7-8. A piece of farmer’s logbook for the validation experiment

7.3 Results

Figure 7-9 shows the distribution index of the observed farm during a full growth period of 42 days. In this figure a sequence of light and dark periods is magnified to illustrate the concept.

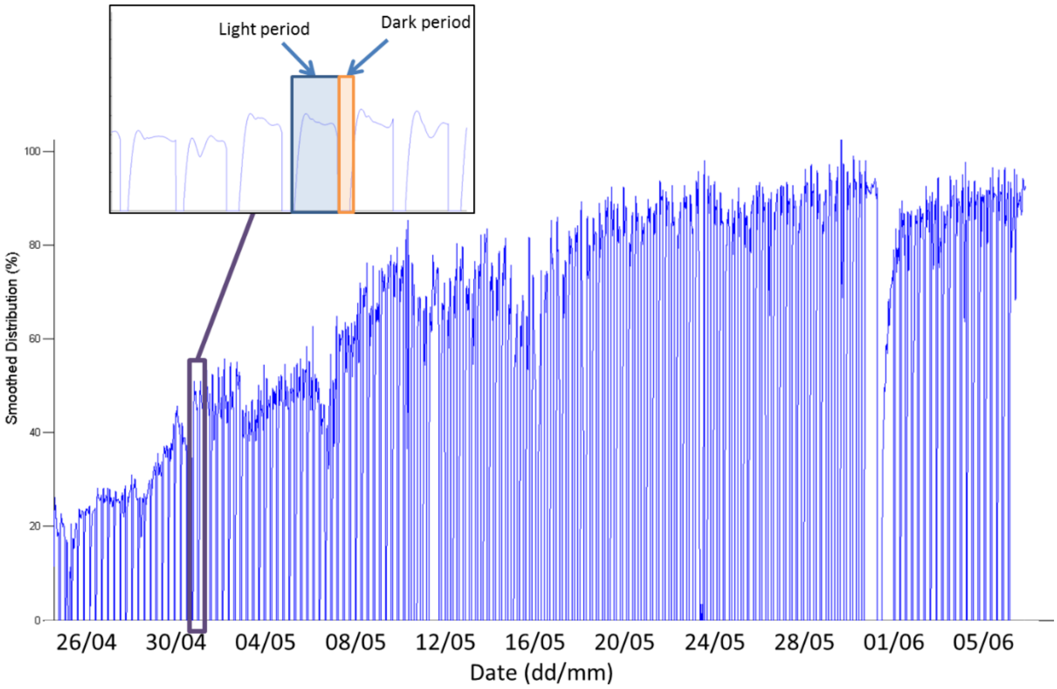


Figure 7-9. Distribution index for the commercial farm from 26/04/2012 to 05/06/2012 (dd/mm/yyyy date format) which is a full growth period of broilers;

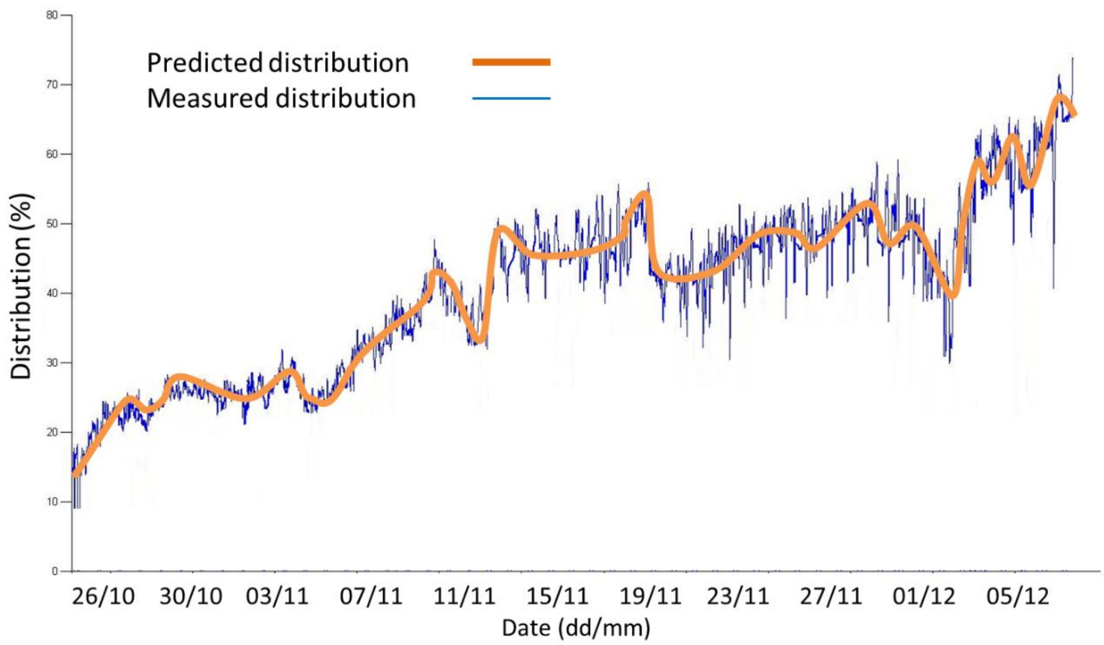


Figure 7-10. Distribution index of the commercial farm used for development of the algorithm; the period spanned from 26/10/2011 to 05/12/2012 (dd/mm/yyyy date format); measured values vs. predicted values;

One of the main challenges in the development phase was that no logbook by the farmer was available, which made it difficult to establish any reference points. Figure 7-10, however, demonstrates that the predicted and the measured values correspond to a very large extent. The model used in this phase was a linear real-time model. Subsequently, in the validation phase (growth period shown in figure 7-11) alerts generated by the algorithm were compared with an events logbook filled in by the farmer.

Figure 7-12 shows an example of applying the prediction model on several light periods of distribution index data. In normal situation (left picture) chickens are well distributed, but as shown in the picture on the right a problem with the feeder line can cause a drop in distribution index since broilers cannot have access to food on that feeder line and spread over the regions close to other feeder lines.

The results of applying the algorithm on the data for a complete fattening period in a commercial broiler farm in the Netherlands are presented in figure 7-13. The algorithm managed to successfully detect 20 (95.24%) out of 21 events in the house. Figure 7-14 provides an evaluation of the algorithm by comparing the alerts it produced with the farmer's logbook. This figure clearly shows that the algorithm has a very high success rate in detecting most of the events, including food and water supply problems and climate control system failures.

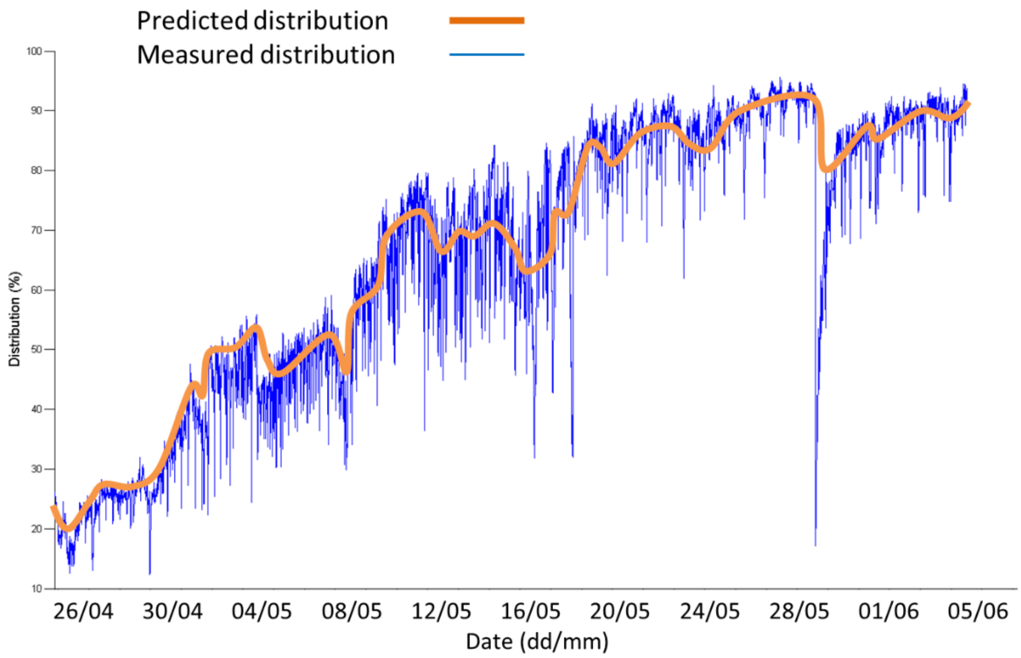


Figure 7-11. Distribution index of the commercial farm used for validation of the algorithm; the period spanned from 26/04/2012 to 05/06/2012 (dd/mm/yyyy date format); measured values vs. predicted values;

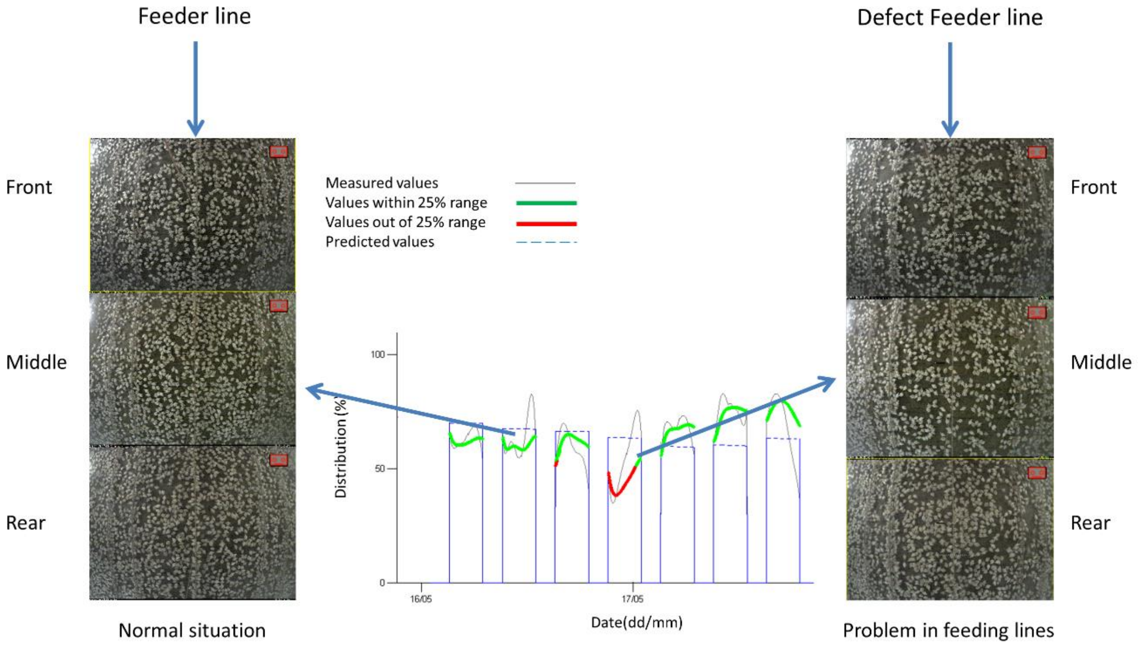


Figure 7-12. Detection of an event by predicting distribution index in a broiler house; dashed line: prediction; dark thick line: alarm region (more than ±25% of deviation from the predicted value); thick bright grey line: less than 25% of negative or positive deviation from the measured values; thin grey line: measured distribution index using the eYeNamic tool

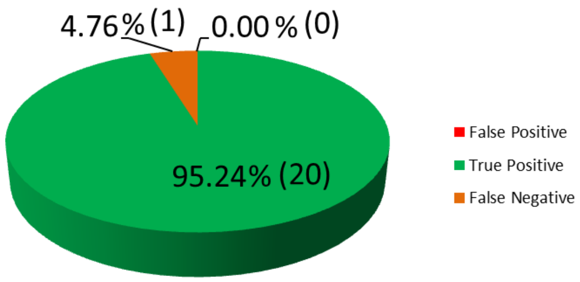


Figure 7-13. Results of automatic detection of events in a commercial broiler house using the eYeNamic data prediction algorithm; the number of events (100%) is the sum of false negative (4.76%) and true positive (95.24%) cases

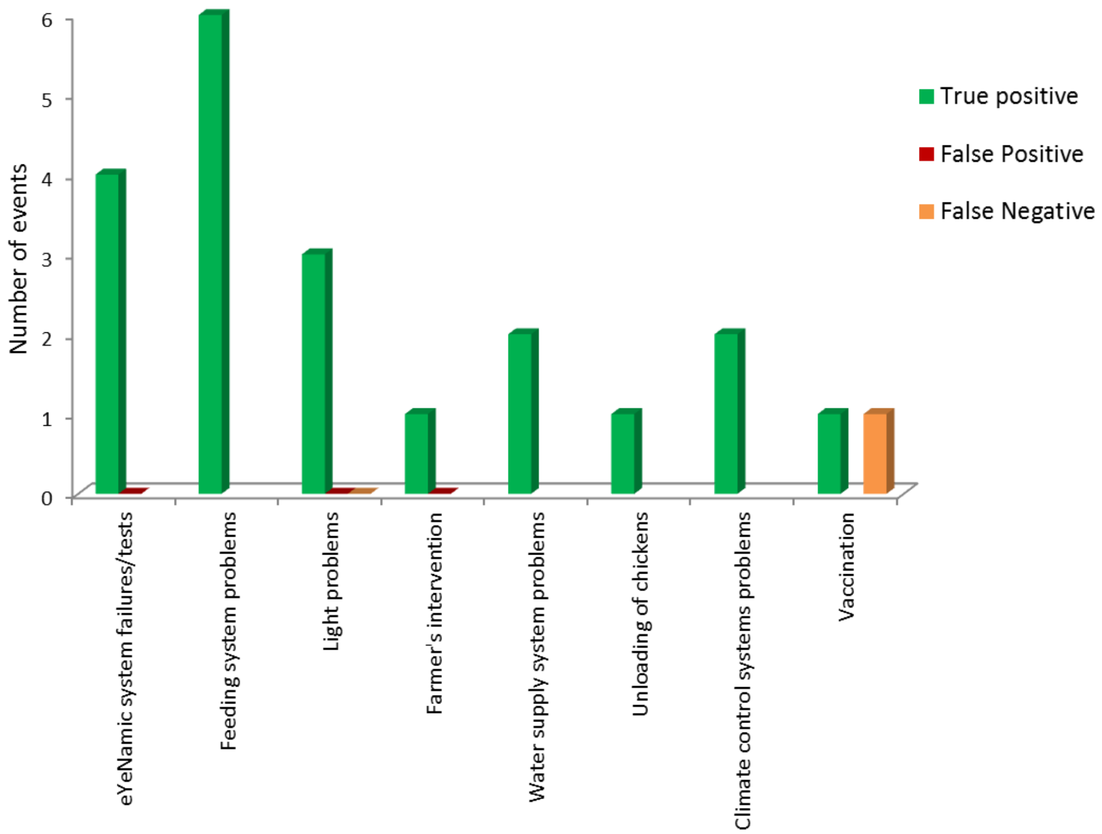


Figure 7-14. Results of automatic detection of events in a commercial broiler house using the eYeNamic data prediction algorithm categorised based on type of the events

7.4 Discussion

Image analysis and real-time calculations are an important step towards the automatic monitoring of broiler chickens. Although the automatic monitoring of animals is a fairly novel approach (Venter and Hanekom, 2010; Kristensen and Cornou, 2011; Maertens et al., 2011), employing these technologies has already proved quite useful to farm managers (DeShazer et al., 1988; Barnett and Hemsworth, 2009). This can mainly be attributed to the broad applications that automated animal monitoring has to offer (Velasco-Garcia and Mottram, 2003). When used in broiler houses, some of the possible applications are the detection of problems associated with feeder and drinker lines, malfunctioning in heating or ventilation and vaccination effects.

Currently, parameters such as temperature are measured constantly in conventional broiler houses. Alarm systems which monitor water intake have also been investigated and made available to farmers (Pluk et al., 2010). However, the commercial use of a monitoring system based on animal behaviour using automated image analysis has not been reported.

The method presented in this study analysed the image distribution index of broilers, which is determined by their complete behaviour and is known to be tied to welfare quality (EFSA, 2012). Such an approach makes automatic detection of abnormal behaviour in broilers more likely. To evaluate the performance of the algorithm presented in this study, its results in detecting the events explained in sections7.2.1 and 7.2.2 were compared with the method proposed by Pluk et al. (2010) that utilised water volume usage modelling. Figure 7-15 compares the results obtained by each method and shows that the method used in this study could detect 95.24% of the events correctly while generating no false alarms. The reference method, however, yielded 6 false alarms and failed to detect 2 of the events.

Our results indicate that this method offers many potential applications to improve animal husbandry management. Although events such as vaccination, which have long-term effects on broilers (Hoerr, 2010), are more difficult to detect, the algorithm still managed to detect 1 out of 2 of these events (the far right columns in figure 7-14).

These results clearly show that the presented algorithm together with the eYeNamic system can be used as a reliable early warning system allowing the farmer to manage his farm more effectively and economically.

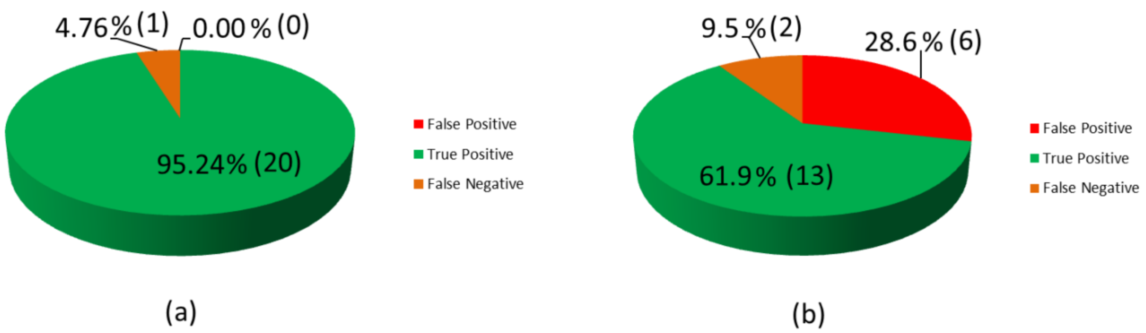


Figure 7-15. Comparison of performance of the presented algorithm in this work (a) with the algorithm presented by (Pluk et al., 2010) (b); true positive cases in (a) are 33.34% more than (b) while unwanted alarms (false positives) are only observed (28.6%) by applying the second method.

7.5 Conclusion

A technology has been found that offers fully automated identification of problems in a broiler house. This was made possible by using real-time camera vision-based monitoring based on topview video processing and linear real-time prediction models. Since the early warning system is one of many functions of the camera used in our design, this algorithm has to be fast enough to be integrated into our real-time monitoring system. Processing time of all the algorithms developed in this PhD is discussed in section 8.2.1.

The results show that, thanks to real-time prediction of the distribution index of broilers, it is possible to detect problems in a broiler house such as malfunctions in feeding, drinking, heating and ventilation systems. In tests, the system has been able to detect these problems with an accuracy of 95.24%, while no unwanted alerts were generated. In conclusion, the method introduced here has considerable economic value for the livestock sector, since feed and water intake, health, welfare, performance and farm profitability are all variables that are important to be monitored. Finally, developing this method will help farmers monitor their animals' behaviour and health more efficiently.

Chapter 8 General Discussion

8.1 Manual assessment of livestock health and welfare indicators

Observing or monitoring animal-based measures can substantially contribute to health and welfare objectives. For scientific purposes, human observations of measures are often taken as reference of recording techniques to assess the level of welfare and health of the animals on farm and at slaughter. These measures are all relevant to behaviour and health or physical status of animals. Therefore, the welfare of animals is often assessed by ethologists or assessors through manual observations based on chosen measures and protocols.

As mentioned in the introduction section, Welfare Quality (Blokhuis et al., 2010) was realised to develop a method for animal assessments. Although this protocol considers assessing several important measures in animal welfare, it relies on manual observations. Results obtained using this method are exposed to subjectivity and may vary from one assessor to another or from one observation to another. Otten et al. (2013) reported that the behaviour-based measurements had a higher degree of within-farm variability than clinical- and resource-based measurements as the assessment involves a greater degree of subjectivity. Moreover, this technique is time consuming and labour-costly. The average time required for implementing the entire Welfare Quality protocol on growing pigs present on farms was 6 h and 20 min per visit (Temple et al., 2011). Although it gives an accurate image to the 12 criteria that constitute animal welfare in a farm, it is impractical to visit a majority of livestock farms due to lack of time. Another problem is that one visit at the end of a fattening period for the limited group of visited livestock houses only gives a momentaneous observation that might vary in time in another visit during the year. This is while a monitoring system should involve a short duration, be relatively easy to perform on commercial conditions and it should require little input from the farmers (Temple et al., 2011).

Another limitation of this yearly assessment is that such approach comes far too late to improve the welfare of the monitored animals but hopefully for the next groups of animals on that farm. This method is not a continuous system with early warnings neither it is sort of a real-time management system that helps the farmer to maintain health and welfare in his herd. In addition, manual assessments could raise hygiene issues. Each assessor visits different farms and may transfer diseases from one farm to another.

Modern sensing technology could facilitate continuous real-time automated assessment of animal welfare additional to health and performance. Cameras, microphones and other sensing systems/sensors can be used to measure and quantify the status of individual animals as well as the group. These techniques can complement the manual measures from the Welfare Quality protocols and the observations of the farmer. This could save time and effort and at the same time provides relevant real-time management information.

8.2 Automatic measurement of livestock health and welfare indicators

Labour costs and long duration associated with manual assessment can be reduced by automating some measures with modern technology. Every second assessment of the animal status and their environment can be achieved in terms of health, welfare and performance. For instance, weight of pigs in the farm can be measured by the farmer using a weighing scale. However, this is very stressful for the animals and it requires taking pigs out of their pen one by one, forcing them to go on a scale and pulling them back to their pen. This is a very difficult process and quite impractical especially for bigger farms. That is why this is only done at slaughter. As an alternative solution, a technician could install a camera for the farmer to not only measure weights of the animals daily, but also find out how the composition of their meat changes over time (Doeschl-Wilson et al., 2005)! Not only can technology be used for measuring animal variables, but it can also help the famer in managing his farm. For instance, early warning systems can assist the farmer and the veterinarians to take early action in case of a disease outbreak.

Various technologies such as sensors, which were originally used for other production processes, are now applicable for monitoring of livestock. A sensor is an electronic device that is attached to the animals whereas a sensing technique is a measuring technique comprising recording signals from a distance without physically touching the animal. For example, an active collar is a sensor, while a lameness detection system with a Charge Coupled Device (CCD) camera is a sensing technique. It makes use of cameras and real-time algorithms in order to quantify specific welfare and health indicators in the captured images. Sensing systems such as cameras are very important in development of integrated monitoring systems for livestock production. They have the advantage of not requiring any physical contact with the animal and without having any influence on the living organism or on any hygiene issue.

Improvement of digital technology, computational power and remote sensing techniques provide many opportunities for livestock production. Technology can assist the farmers tackling the problem of human subjectivity in animal assessment and offers every second acquisition and interpretation of data. More detailed information is attained from continuous sampling and real-time analysis than human senses can achieve from a yearly visit or limited periods of observation. In order to make automated measurements, the results of the method should be easy to use, inexpensive, quantitative and robust. An integrated monitoring system collects continuous and non-intrusive information from the animal, processes the data and gives early warnings and recommendations to the farmer in a fully automated way.

In many cases, frequency of collected data is crucial for effective monitoring. Although physical variables such as weight are better to be monitored in span of days, most behaviours have to be measured every second. Changes in the normal behaviours, development of abnormal behaviours or other physiological indicators of welfare can only be captured by appropriate frequency of sensing the animals. This helps acquire detailed information on what is happening in reality. By frequent monitoring of specific risk parameters, low animal welfare can be predicted and appropriate measures can be taken. In comparison, increased frequency of the visits to the farm for more frequent data would be costly, laborious and might bear a risk for disease transfer between farms.

In recent years, **Image Processing Technology** has been tested for collecting frequent data in a farm and for assessing welfare status in livestock. For instance, Sergeant et al. (1998) measured every second locomotion of broiler chickens as an indicator of their overall health and welfare status. Moreover, according to Van der Stuyft et al. (1991), image processing systems can be used for the production market, but more specialised research systems are needed to track animal behaviour in research studies with custom animal housing and specific data collection requirements (Lay et al., 2011). Image processing technology is under development in PLF and in supply chain management to identify (Kashiha et al., 2013b), track (Kashiha et al., 2014), and monitor behaviour and health status of livestock and poultry (Yang et al., 2010; Kashiha et al., 2013c). Image processing systems comprise a camera connected to a PC via a capture card. Captured videos are then encoded and recorded on an external hard drive. These videos are either analysed on the spot or subsequently decoded and analysed.

The use of image processing technology has been extended to **animal behaviour and welfare research** because it offers tools to monitor and to obtain feedback on animal location and resource utilisation. For instance, image processing tracking systems have been proved as effective to monitor animal feeding and/or drinking behaviour (Kashiha et al., 2013a), growth (De Wet et al., 2003) and activity (Leroy et al., 2006; Calvet et al., 2009).

Video recording and image analysis techniques offer high potential for management and production control on the farm and for feedback of management advice to the producer. A camera acquiring many images each second can detect information at a higher speed than the human eye. Camera image acquiring works differently from human observation. The human visual system is easily misled and can only recognise about 30 levels of grey while standard image formats have 256 levels or more. With the growth of computing power, it is possible to perform more and more complex processing on more and more images.

For livestock monitoring, video recordings and image processing techniques can complement the farmer or the veterinary in detecting small but important **changes in behaviour**, predict abnormalities and detect events early, give warning signals so that the responsible person may take charge. Especially with growing size of farms and animal groups, image processing can assist in on-line detection of each and every animal during their growth. Automated monitor tools based on video could give information as valuable as physiological tests or ethological observations.

In **Chapter 2**, it was explored how pigs could be identified in experimental conditions in a fully automated way based on continuous image analysis. This was important since it was for the first time that pigs could be tracked using marks stamped on them and without need for attaching sensors to them. This was one of the least intrusive ways of tracking animals in order to do behavioural analyses.

Methodology of tracking the pigs was based on a geometrical model**. The image geometrical model** helps find steady-state **location** of livestock. For applications where only location of the animals is needed, an **ellipse** (geometrical model) could be a good fit. It is a simple model, ignoring details of body parts and tracking the localised animal within a pen accurately. It is also independent of type of the animal and could be applied to many animal species. An ellipse includes several **parameters**: a centroid (central point of animal topview image), a major axis (an approximation of animal's body length), a minor axis (an approximation of animal's body width) and orientation (angle between major axis and horizontal line) (Leroy et al., 2006). These parameters help to distinguish animals from background and other objects in the pen and also provide useful information on **animal behaviour** e.g. feeding, drinking and resting via zone appearance.

Some of the possible applications of the introduced tracking method are calculating the number of times each pig drinks or feeds, how long each pig stays at the drinker or the feeder, how frequent each pig visits the feeder or the drinker, monitoring the trajectory of pigs movement in a pen or analysing individual agonistic behaviours of pigs.

Resting behaviour, as an application of the tracking method introduced in Chapter 2, was monitored. This gave us an impression how individual pigs spend their time in their resting zone. In addition, this analysis helped to understand how unique resting behaviour among individual animals is. This is closely correlated with activity level in animals.

Activity level of individual animals is a key to their performance and good welfare (Beker Yousuf, 2006). Welfare issues can lead to pain and suffering in livestock. Pain and suffering are forms of stress on livestock and stressed animals can show compromised growth, production and reproduction (Lauber, 2007). Animals experiencing pain normally **deviate from their normal behaviour** by **altering locomotion** (either an increase or decrease) (Anil et al., 2002). This deviation can be detected and reported to farmer using automated tools, thus avoiding a compromised growth.

Although earlier studies involved innovative technologies that could be utilised to monitor pig locomotion, many of them require animals to be fitted with sensors or tags. In **Chapter 3**, monitoring unmarked pigs' locomotion in a group-housed environment through automated quantification of locomotion levels using continuous image analysis was investigated. Monitoring animal locomotion in a group is an essential aspect of analysing different behaviours. Moreover, this technology can help to monitor a large number of welfare measures taken to improve the animal welfare. Hence, there are many possible applications for which the use of this technique can be of benefit to livestock.

Thus **not only location** of the ellipse model, but also **dynamics of its movement** provide valuable information on animal behaviour (Leroy et al., 2006). In Chapter 3, **Locomotion** of pigs was quantified by measuring linear and rotational movement of the ellipses. **Image geometrical model** could be used to monitor locomotion. Two parameters were added to the **ellipse model** used in Chapter 2: **angular movement** and **linear movement**. Visual observations were taken as a reference with accuracy of 20 cm for linear and 15 degrees for angular movement. These movements help to measure certain animal behaviour such as **chasing** (rotational movement) where a pig tries to avoid another intruding pig and **running or walking** on a straight line (linear movement). Comparison of automatic measurement with visual observation showed that locomotion could be measured in real-time by the ellipse with an **accuracy of 89.8%**. These results prove that the ellipse model is accurate enough in monitoring animal body movements. This research is a step ahead in measuring locomotion since, unlike previous research works (Leroy et al., 2006), locomotion calculated in this way is independent of weight and size of the animals, so one or two overactive animals (with high locomotion) cannot compensate for their underactive pen-mates (with low locomotion).

Although locomotion and occupancy of a certain zone is important in assessing the status of animals, **understanding the motivation why the animal attends the zone** is **more relevant to interpret animal behaviour**. Behaviour is used to assess health through the clinical and pre-clinical assessment of pain, injury and disease. It also is truly important in gauging what animals' needs are. This is not only carried out through on-farm assessment, but also through the use of choice and **preference tests as a response to environmental variables** (Kirkden and Pajor, 2006; Scholz et al., 2010).

In the next step, we were considering if **tracking and localising** animals would allow monitoring **behavioural response** to an environmental variable**. Chapter 4** discussed how animals behave when given choices to move between pen zones with different environmental conditions. **Image geometrical model** facilitates understanding how animals will behave in such conditions. In a case study, **laying hens** were monitored while moving between compartments with different **ammonia concentrations**. Hens, **as elliptical geometrical models**, were tracked while being free to choose to stay in one of 4 compartments in a preference chamber. The time spent in each compartment and their trajectory was registered. During a choice-test study, mean ± SD success **detection rates were 95.9 ± 2.6%** for an individual bird when measuring compartment occupancy. Although no strong link between compartment occupancy and high ammonia levels was identified, ellipse fitting algorithm showed its potential as a reliable method for assessing preference tests. It should be noted that this model was essentially the same one used for monitoring zone occupancy for pigs. Therefore, it can function independent of animal type.

The animal's choice can be linked to preferences for certain conditions under which they may perform better. In the aforementioned case, elevated ammonia concentrations over a few days can cause drop in performance in laying hens: namely egg production.

The **geometrical (elliptical) model** can not only be used for behavioural analyses such as preference tests, but also helps extract **physical variables** such as **body weight** from the image. Although body weight, as an important indicator of performance, should be monitored at all times, it is more crucial to be measured in compromised living conditions. It is especially important to detect any **compromised growth** due to **abnormalities in environmental conditions**. In this case, weight could be estimated using an **image geometrical model**, namely **topview body surface dimensions** of animal's body.

A daunting challenge for famers and animals is expensive and stressful hand weight measurements. Thus, it is recognised that an accurate method of weighing pigs on a regular basis non-intrusively and without the need for labour input would be a great tool for livestock producers. In **Chapter 5**, **animal weight estimation** of pigs using VIA was analysed. This method relies on **a single camera** as a sensor installed above a pen to estimate animal's weight through topview body area measurement and dynamic modelling. The biggest **advantage** of the method is that no labour input is needed and the animals are not required to be bothered or stressed during the measurement. The introduced method can make substantial profits for livestock enterprises because continuous information on daily weight would allow farm managers to optimise nutritional management practices, predict and control slaughter weights, and potentially assist in monitoring and improving herd health. However, similar to other technologies, there are **disadvantages** with this method too. First is the cost. Although the sensor as such is cheap, complete image acquisition systems (including cameras, capturing devices, storage and processing units) are rather expensive in particular if implemented on the whole farm. Second is the need for careful maintenance. Dust, dirt, insects, moisture can lead to failures in the image acquisition system.

VIA uses aerial-view images of animals provided by cameras to determine **body surface (geometrical model)** dimensions and may be used for real-time monitoring of pig weight. An ellipse model was again used to extract pigs in an image. In a next step, **topview body area** enclosed inside the ellipse was extracted and a second ellipse fitted to the head part was excluded. This helped to extract corpus area of the pigs accurately. **TF modelling** facilitated linking body weight with the extracted corpus area. Combination of ellipse fitting and TF modelling made it possible to estimate pig's **body weight** with a **standard error of 0.82 kg** which outperforms conventional methods such as linear regression (SD = 4.52 kg) and mixed effect (SD = 2.68 kg) models in the weight range of 17-45 kg. Therefore, weight as the **most important indicator of performance in fattening pigs**, could be estimated and monitored every second only with 2D images and without need for depth information or composition of pig's body shape. However, this method has drawbacks too. The most important one is the frequent calibration it needs for updating model parameters. If these parameters are not updated every few days, prediction weights might deviate from measured ones. This is because transfer function model cannot be adaptive enough to cope with image boundary variations for weight prediction over a long period of time. Another drawback of this method is that angle of view could affect accuracy of weight estimation. For angles greater than 30 degrees compensation is necessary and this will increase processing time.

Another indicator of solid performance is **drinking behaviour** and **water volume usage** which are closely related to feed intake and health status (Gonyou, 1996). In **Chapter 6** we explored the possibility of an automated monitor tool for **water volume usage** by pigs in a pen. **Image geometrical model** could help to estimate water volume usage through identifying the pigs while drinking. This becomes possible by fitting two **geometrical (elliptical) models,** one to the corpus and one to the head in order to determine the direction of the animals. A water monitor tool could not only estimate the actual water volume usage of pigs, but could also monitor **drinking behaviour**, i.e. **frequency of drinking visits and duration of drinking**, which is known to be related to other behaviours such as feeding (Fraser, 1984; Bigelow and Houpt, 1988; Morgan et al., 2000). Moreover, abnormalities in its dynamics could be linked to health and welfare problems. Therefore, it can be said that data obtained at a high frequency camera capture (1 frame per second in this case) reveals dynamic information for detecting fast changes of active behaviour due to health or welfare problems.

Certain physical variables such as **water volume usage** are only possible to be monitored in **specific zones.** Drinking behaviour of pigs was studied in **Chapter 6** by using the geometrical (ellipse) model for localising the pigs and for detecting them at the drink nipple. **Hypothesis** was that through measuring drinking behaviour (duration and frequency of drinking bouts), water volume usage could be estimated. Opposite to the weight estimation algorithm, in which the head ellipse was excluded, the **head ellipse played a pivotal role**. Pigs tended to play around the drink nipple or lay down in front of it. In many cases, pigs were present in front of the drink nipple, but were not headed to it. So, these cases had to be excluded from analysis. Therefore, the ellipse model was extended to **two ellipses: head and corpus ellipse**. Furthermore, **contour analysis** was done to detect the ears since ears are the most obvious body parts in detecting the head in pigs. For the purpose, distances of the body border pixels from centroid of the body (ellipse) were analysed and by analysing profile of these distances, **ears were distinguished** from tail side. In addition to the ellipse model, **geometrical features of the body contour** were employed to discover direction of the animals at the drink nipple. Using this technique, not only could drinking behaviour be measured, but also the **actual water volume usage could be estimated**. Similar to Chapter 5, TF modelling was used to make **a link between the image features (drink nipple visits) and a physical variable (water volume usage).** Since half-hourly water volume usage could be estimated with an **accuracy of 92%** (average error of **220 millilitre**), this algorithm could be an alternative for conventional water meters to reduce the number of sensors.

Welfare monitoring using image analysis could be performed not only at individual level but also at **group level**. This applies to weight gain and drinking behaviour previously discussed. However, **flock behaviours such as "distribution of animals" are only meaningful at group level**. **Image geometrical model** could measure group level animal behaviour (such as distribution), interpret it and warn the farm manager of behaviour abnormalities to avoid negative implications on animal performance.

Chapter 7 dwelled on how measuring and predicting animal distribution could serve as an early warning to avoid animal harm and production losses. **Distribution index of broiler chickens** is calculated by measuring how topview body areas occupy a grid of zones dividing the image equally. In this case, area occupied by **geometrical (elliptical) model** fitted to each individual is used to calculate object area of the whole group and therefore the distribution index. A linear **real-time input-output model** was developed to test the **animal distribution index in response to light input**. Broilers were monitored during a complete growth period (42 days). As broilers grow, they occupy more floor space and object (broiler) size increases. Greater object size means smaller moving space and less probability of the ground being visible. Thus distribution increases over time almost linearly. Based on this, a model was developed to predict future distribution index. Any drop in the measured variable could be interpreted as certain zones (e.g. feeders or drinkers) abandoned in the house which could be linked to a problem in that zone. Measured distribution index which deviated from prediction for more than 25% notified the user of a problem incident in the broiler house. Using this methodology, **95% of events occurring in a commercial broiler house, e.g. problems associated with feeding and drinking lines, were reported** while no false alarm was given. Therefore, **combination of the ellipse model with prediction models** could also work at group level.

Distribution index could be used to monitor broiler welfare too (EFSA, 2012). Abnormal variations in distribution index could be linked to welfare issues. In this work, a method was described for early warning of events in a commercial house measuring the distribution index of broilers and a real-time monitoring technique. The **objective** was to develop a system that could report malfunctioning in a broiler house to the farmer in real-time. The results obtained from this work proved that many welfare disturbing events such as problems associated with water and feed supply, lighting problems and climate control malfunctions could be detected using merely images captured using a topview camera, measuring distribution through image processing and applying prediction models. **Modelling** was an essential part of this research work which helped to interpret the features extracted from image and to make predictions based on existing measured data.

Having all the techniques and materials in mind, it was learned that a general methodology, namely **image geometrical model**, could be employed to measure many variables in livestock daily life. This was a vital and novel contribution of this PhD which led to devising several monitoring algorithms. In addition, we had the opportunity to apply this in practice. For instance, the early warning system researched in Chapter 7 has been tested in a **commercial farm** in the Netherlands and may lead to a commercial product.

A second discovery of this PhD was that a single sensor, namely camera, could be used to monitor many different variables. Using such a solution, the farmer will only need to install one sensor to collect extensive data and assess the status of his animals. However, there are variables such as vocalisations that a camera cannot capture. For such variables, additional sensors such as microphones would be needed.

Having a multi-function sensor and a general methodology in data analysis can be seen as a basis to measure useful variables in livestock houses. However, for interpreting the measured variables, applying mathematical modelling was essential. Next section will discuss how mathematical modelling could help convert mathematical variables to physical and meaningful variables relevant for farmers and caretakers.

8.2.1 Computation time of the algorithms

All the algorithms discussed in the previous chapters have to run on a processing platform connected to a camera. Therefore, it is important that these algorithms are fast enough to be integrated into a real-time monitoring system. In this section performance of the algorithms is assessed in order to find out if they can run simultaneously to produce results in real-time.

The processing platform for all the algorithms developed in this PhD was a desktop PC with Intel Core2 Duo E7200 2.53 GHz[1] CPU[2], 6 GB of RAM[3] and 64-bit Windows 7 operating system. Codes were developed in MATLAB environment. Table 8-1 shows the computation time for each algorithm.

Table 8-1. Computation time and memory occupied by the algorithms developed in this thesis

Algorithm	Computation time (seconds)	Memory (Megabytes)
Identification	0.23	85
Locomotion	0.58	112
Tracking	0.84	142
Weight estimation	0.62	140
Water volume usage estimation	0.72	108
All above algorithms at the same time	2.54	762

[1] Giga Hertz
[2] Central Processing Unit
[3] Random Access Memory

Since all the algorithms are supposed to work at the same time, above figures promise providing results with a maximum delay of 2.54 seconds which would be quite feasible for livestock applications.

Without proper modelling interpretation of processed images will not be possible. Feature variables extracted from images have to be linked to target variables using model parameters so that a biological variable could be defined mathematically. Next section addresses application of these models in this thesis.

8.3 Using mathematical modelling techniques for monitoring and predicting health and welfare related responses of livestock

Livestock responses can be analysed using mathematical modelling methods. These models (Ljung, 1987; Young, 2011) provide information on the dynamics of the past data and can be used for predicting future data. These predictions can be used to develop model-based monitoring. This has been done in Chapters 5 and 7. Chapter 5 discussed how **modelling could be used to link topview body area of pigs with their actual body weight**. In Chapter 7, a **short-horizon linear model was used to predict distribution of broiler chickens**. Subsequently, this was utilised to detect future irregularities in distribution which helped to detect abnormal behaviour in broilers.

Physiological processes in animals can also be described by data-based models. These models have a simple structure and are characterised by only as many parameters as can be justified by the information content of the available data. However, the data-based models have no direct physical or biological meaning, but there is an intermediate type of model: **the data-based mechanistic model**. In these data-based mechanistic (or grey box) models, the structure is obtained by some form of objective statistical interference but the resulting model provides a description that has relevance to the physical or biological reality of the system (Young, 1993).

Livestock responses, such as weight gain may easily be identified with data-based models where no prior knowledge is necessary. Data-based models are inferred and the model parameters are estimated by reference to the experimental data using more objective, statistically based methods. The model parameters can be estimated on-line during the process, resulting in an adaptive model that can cope with the characteristics of most biological processes (Goodwin and Sin, 1984; Aerts et al., 2003a).

In Chapter 5, it was intended to find the best model to describe the relation of the weight of pigs with their topview body area, in order to estimate the end-weight of the animals and to monitor their growth. The input of the system was topview area measured by a camera together with an image processing algorithm and the output was weight of the pigs. Sampling frequency was one sample per second. Twice a week weight measurements using a scale were taken as a reference and were used to set the model parameters. Due to variations in posture of the pigs and in illumination during the day, a median of each second measurements was calculated. Then different **data-based modelling** techniques were analysed and compared for estimation of the body weight of pigs. Estimations were carried out using three methods, namely linear regression and mixed effects (non-linear) models as reference and **single input-output TF model** as the proposed method. The TF model yielded a higher **R^2 (0.975)** compared to 0.871 for linear regression and 0.943 for mixed effects and a lower SD of 0.82 kg compared to 4.52 kg for linear regression and 2.68 kg mixed effects. This clearly demonstrated that this method can estimate body weight with a higher accuracy and reliability.

In Chapter 7, a **linear input-output and real-time model** was developed and tested to model the animal distribution index in response to light input. As the animals grow, the number of object pixels increase and visible floor space decreases. In normal conditions, less visible floor space is linked to a higher distribution index. Theoretically, when chickens grow so much that they cover all the floor space, distribution index will be 100%. Therefore, any abnormal drop in distribution index could be linked to an event. Using this model, the animal distribution index could be predicted online. Comparing these predicted values with the real-time measurements makes it possible to detect any malfunctioning (technical failures during a fattening period). Results showed that this method could report **95.24% of events in real-time**, demonstrating a high potential of using automatic monitor tools and data-based modelling for broiler production over a complete growing period.

Thus, it was found that data-based input-output models can be used in different production systems for different purposes such us accurate fitting for estimation of weight in pigs and prediction of the distribution in broiler chickens. This takes place due to the fact that data-based modelling techniques update themselves with and according to the data, and that these techniques are used with a short prediction horizon.

Chapter 9 Conclusions

Continuous real-time monitoring of farm animals is the basis of new management systems for farmers. This means that the fully **automated monitoring** of animal health, welfare and productivity is the **key element for the farmer to guarantee animal health and welfare, and to increase his income**.

An important technique for automated monitoring of animal health is real-time image processing. The **first hypothesis** of this thesis was that real-time image processing allows quantifying several variables and behaviours on animals using one single sensor, namely a camera. Quantifying animal variables demands developing proper models. The **first objective** of this thesis was to analyse how physical and behavioural variables could be measured in real time using image processing. This was researched using a **generic geometrical model.** Physical variables in livestock environments could be indirectly measured accurately using image processing which is a main technique of PLF. Animal responses were automatically monitored in real time with capturing and analysing image data with a sampling frequency of one sample per second. The **second hypothesis** of the work was that **physical variables are linked to behaviours** and this link could be established through image processing technology and dynamic modelling as shown in figure 9-1.

The above objective was achieved as automatised monitoring using a camera sensor in the farm enabled development of **early warning systems** as well as **modelling behaviours and physical properties** of animals as done in this thesis. Furthermore, welfare and health related responses of animals could be monitored, measured and interpreted through monitoring behaviours and physical variables.

With data collected from image acquisition systems, **input-output modelling** could expose in an on-line way changes induced in the system due to either environmental factors or animal induced factors. The key element was that **detections and predictions could be achieved in an on-line manner** in the field.

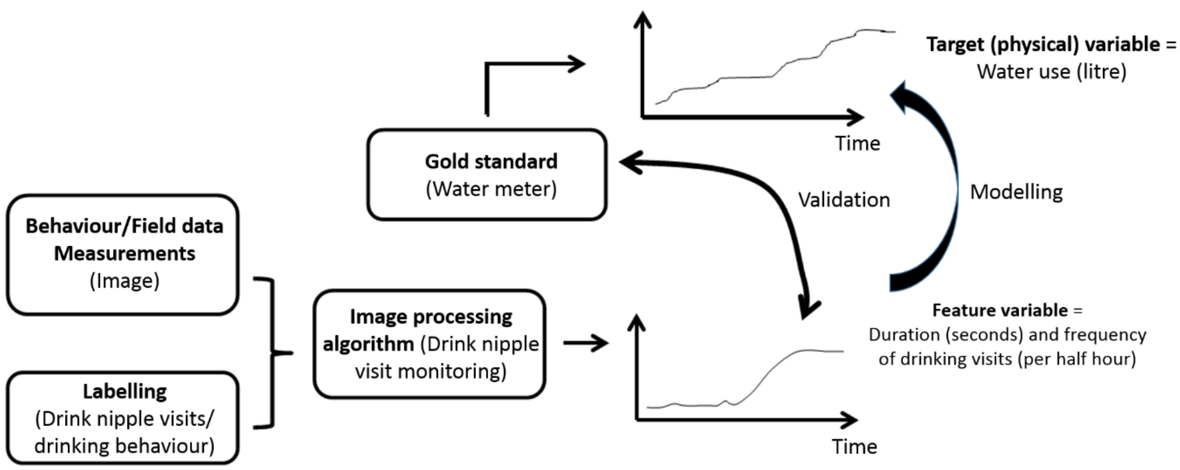


Figure 9-1. From behaviour (e.g. drinking) to physical variable (e.g. water volume usage) in PLF sensor technology; general scheme courtesy of (Berckmans, 2013)

Technology of **high data rate acquisition and processing** was crucial. Changes were detected or predicted immediately so that the farm manager or a person experienced in animal physiology can have an indication as to what is happening. **Early warning, prediction of future data, processing of dynamic data** and making a direct link with animal welfare measures were proved to be clear advantages provided by vision technology to livestock production.

Monitoring of animal welfare, health and performance needs an **appropriate frequency of automated measurements**. The manual measurements, however, were necessary for validating data analysis. The next phase after validation was always analysing the whole data of the experiments for behavioural analyses.

In **Chapter 2**, the method of Shape Identification was applied to **track pigs in different zones** in order to monitor **behaviours** of pigs in a pen **in group and at individual level**. Individual data analysis enables assessing welfare and health of each animal and this could help to avoid outbreak of diseases or abnormal behaviour of a few pigs affecting the rest of the pen-mates. Therefore, monitoring of individual pigs can give earlier alarms raised by a certain problem. A total of 40 pigs were divided into four pens and were monitored every second from 07.00 h – 19.00 h during 13 days. **Geometrical (ellipse) model** was fitted to the pig images in order to track and localise them within a pen and certain zones in the pen. In the analysis carried out, identification was carried out with an accuracy of 88.7%.

Behaviours of pigs based on the zone they choose to attend in a pen could also be analysed using the introduced method. One analysis provided in this chapter was the **resting behaviour**. From manual observations it is known that pigs rest in more than 96% of cases in the resting zone. Currently, this method could detect the pigs that rested more than the others. Moreover, there are many applications for identification, tracking and locomotion monitoring using the presented technique. The introduced method might contribute in future as an important and economically relevant tool in livestock husbandry since feed intake, health, welfare and performance are all variables that are important enough to be monitored on animal individual level.

Another behaviour that is important to be monitored for individuals and group is **locomotion**. Monitoring animal locomotion in groups is an essential aspect of analysing different behaviours. Moreover, this technology can help to monitor a large number of welfare measures such as “ease of movement” and “thermal comfort”. Hence, this technique can be useful for many possible applications.

As presented in **Chapter 3**, pigs could be tracked and their speed and location could be registered. This was the first time that automatic detection of the locomotion of unmarked pigs in a group could be carried out by image processing. It was shown that pig locomotion detection is possible by localising individual pigs in the group by fitting **geometrical models (ellipses)** onto their topview body image and tracking those ellipses over time.

While this method is dependent on contrast between floor and pig surface it could still detect IL pigs with an accuracy of 89.8% thanks to its robustness against body shape variations.

In conclusion, this method might contribute in the future as a practical tool in livestock husbandry since health, welfare and performance are all variables that are related to improving locomotion.

Algorithms such as locomotion measurement **could be applied to different livestock species**. To serve this purpose, as presented in **Chapter 4**, a similar algorithm used for measuring locomotion in pigs was applied to **laying hens**. An EPC was designed comprised of four stainless steel compartments. The four EPC compartments were interconnected by passageways which allow a test bird to walk from one compartment to either of the adjacent ones. A video camera was mounted from each cage's ceiling above the bird area. Images captured were analysed by an IPS which segmented images and tracked hens transiting through compartments. Each camera covered the entire test bird area of a compartment during a choice-test study, **mean ± SD success detection rate** was **91.0 ± 2.6%** when measuring compartment occupancy. In this application occupancy analysis was used to track the hens while they were exposed to different ammonia levels at compartment level.

In conclusion, the IPS system is suitable for determining the total time hens spend in each EPC compartment, frequency of visits and related behaviours such as feeding or resting. Moreover, the **geometrical model** (ellipse) fitting algorithm proved to work independent of the studied animal. This happens mainly due to the fact that an ellipse model simplifies animal's image and facilitates localising animals by calculating only a few parameters.

The **final objective** of real-time monitoring of livestock using image analysis is to **assist the farmer and stocks personnel to manage their animals in a more efficient way**. Weight measurement is one of the most challenging and labour-intensive tasks of daily farm management. One of the most important measurements an IPS could perform is **weight estimation**. In **Chapter 5**, a technique has been introduced that offers fully automated weight estimation of pigs. The results show that by **measuring topview body area** and adapting a **TF model**, it is possible to **estimate BW** with an accuracy of **97.5% on group level** and **96.2% on individual level.** In conclusion, application of the introduced method can bring significant profits for livestock enterprises since continuous information on daily weight would potentially assist in monitoring herd health.

Although monitoring physical specifications of animals would be helpful for farmers, analysing behaviours is no less important for animal scientists and therefore an **important objective of this thesis** was monitoring **behaviour of animals** at each second. To fulfil this objective, in **Chapter 6**, **drinking behaviour** of pigs was studied. Additionally, **as the most remarkable finding of this PhD**, it was discovered that a **behaviour** such as **drinking** could help to **estimate a physical variable** such as **water volume usage** of pigs with an accuracy of 92%, thanks to an accurate image processing algorithm and a TF model developed for this purpose. As such, this method offers many potential applications to enhance animal husbandry management.

The **third hypothesis** of the thesis was that measuring and monitoring **individuals and group of animals** would be of importance and emphasizing on either of these depends on the data quality and objective of the behaviour analysis. While tracking individuals is important for assessing behavioural responses of animals, **group behaviour** can be meaningful too. In **Chapter 7**, a technology was introduced that offered fully automated **identification of problems in a broiler house** by studying group of broilers. This was made possible by using real-time camera vision-based monitoring based on topview video processing and linear real-time prediction models. The results showed that, thanks to **real-time prediction of the distribution index** of broilers, it is possible to detect problems in a broiler house such as **malfunctions in feeding, drinking, heating and ventilation systems**. In tests, the system has been able to detect these problems with an accuracy of **95.24%**, while no unwanted alerts were generated. In conclusion, the method introduced had considerable economic value for the livestock sector, since feed and water intake, health, welfare, performance and farm profitability are all variables that are vital to be monitored. Finally, developing this method will help farmers monitor their animals' behaviour and health more efficiently.

Precision Livestock Techniques that benefit from Image Processing Technology lead to more frequent monitoring and modelling of many health and welfare related responses of livestock. In addition, analysing the data at different abstraction levels helps measure different behaviours (e.g. locomotion and resting) and also several physical variables (e.g. weight and water volume usage). **The most remarkable finding of this PhD** was that monitoring behaviours (e.g. drinking behaviour) frequently using Image Processing Technology could help to estimate relevant physical variables (e.g. water volume usage) of livestock with a high accuracy. This was achieved by devising accurate behaviour monitoring algorithms and dynamic data modelling as shown in **Chapter 6**.

It was demonstrated that the **variables in livestock life are closely related**. This close relationship was **mathematically defined in this thesis**. Specifically, physical variables that each conventionally need a sensor to be measured could be indirectly estimated accurately. For this purpose **correlation between behaviours and physical variables** was investigated. This link was then established through an intermediate (feature) variable obtained from the image processing system and fed to a dynamic model (see figure 9-1). Several applications were explored to reduce workload associated with manual on-farm assessment by the automation of some measures using modern vision technology. The modelling together with on-line measurements were integrated in an analysing algorithm to achieve on-line monitoring of animal health and welfare.

These automatic monitoring techniques developed can be used to complement the manual welfare measures and provide the farmer with relevant management information. Specifically, early warning systems can assist the farmer and the veterinarians to take early action for securing health and welfare of farm animals.

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Curriculum Vitae

Mohammad Amin Kashiha was born in Tehran, Iran on March 5, 1983. He received his Bachelor degree in Electrical Engineering from Iran University of Science and Technology in 2004 and his Master's in Electronic Engineering from Tehran Polytechnic University, Iran, in 2006. From 2006 to 2011 he worked for Niroo Research Institute which is a leading R&D organisation in power industry in Iran. From 2011 to 2015, he has been a doctoral student and a research engineer in M3-BIORES research group at the department of Biosystems in the faculty of Bioscience Engineering of the University of Leuven. He was involved in several projects, including from 2011 to 2013 in a product development project together with Fancom B. V. (The Netherlands), a worldwide market leader in computerised systems for the agricultural sector. Between 2011 and 2013 he participated in Pig Welfare Monitoring project. During these periods he developed several algorithms for monitoring welfare of fattening pigs and broiler chickens. Meanwhile, he collaborated with several international research groups including AWES at University of Illinois at Urbana-Champaign and Swedish University of Agricultural Sciences. These collaborations concluded in bilateral agreements, common publications and new algorithms for monitoring broilers and laying hens. As the last work in his PhD, in 2014-2015 he worked on "precision feeding for pigs" project together with several industrial partners including Fancom and Agrifirm Belgium. In order to pursue his work, he would like to act as a link between industry and academia.

List of publications

Articles in peer reviewed international journal publications

1. Vandermeulen, J., Bahr, C., Tullo, E., Fontana, I., Ott, S., Kashiha, M., Guarino, M., Moons, C., Tuyttens, F., Niewold, T., Berckmans, D. (2015). Discerning pig screams in production environments. PLoS One; 10(4):e0123111

2. Kashiha, A., Bahr, C., Ott, S., Moons, C., Niewold, T., Tuyttens, F., Berckmans, D. (2014). *Automatic Monitoring of Pig Locomotion Using Image Analysis*. Livestock Science, 159, 141-148

3. Kashiha, M., Green, A., Sales, T., Bahr, C., Berckmans, D., Gates, R. (2014). Performance of an Image Analysis Processing System for Hen Tracking in an Environmental Preference Chamber. Poultry Science, art.nr. 4078.

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