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Development of automated computer vision systems for investigation of livestock behaviours

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Development of automated computer vision systems for investigation of livestock behaviours

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List of acronyms

2D	Two Dimensional
3D	Three Dimensional
AM	Ante Meridiem (before midday)
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ARST	Around the Room Set Temperature
AUC	Area Under the Curve
Ave	Average
BCS	Body Condition Score
CCD	Charge Coupled Device
CCTV	Closed Circuit Television
DT	Delaunay Triangulation
Ed	Euclidean Distance
f	Frame
FAO	Food and Agriculture Organisation
FN	False Negative
FP	False Positive
fps	Frame Per Second
GPS	Global Positioning System
H	Head
HRST	Higher than the Room Set Temperature
IR	Infrared
kg	Kilogram
LDA	Linear Discriminant Analysis
L_{max}	Maximum Length of side of triangle
L_{min}	Minimum Length of side of triangle
LRST	lower than the Room Set Temperature
MATLAB	Matrix Laboratory
Max	Maximum
MHI	Motion History Image
Min	Minimum
min	Minute
MLP	Multilayer Perceptron
MSE	Mean Square Error
MVL_{max}	Mean Value of Maximum Lengths
MVL_{min}	Mean Value of Minimum Lengths
MVP	Mean Value of Perimeter

PC	Personal Computer
PM	Post Meridiem (After noon)
RFID	Radio Frequency Identification
RGB	Red, Green, Blue
ROC	Relative Operating Characteristic
ROI	Region Of Interest
S	Side
SAS	Statistical Analysis System
SD	Standard Deviation
SEM	Standard Error of the Mean
SIFT	Scale Invariant Feature Transform
SPSS	Statistical Package for the Social Sciences
SURF	Speeded Up Robust Features
SVM	Support Vector Machine
T	Tail
TN	True Negative
TOF	Time Of Flight
TP	True Positive
UK	United Kingdom
USA	United States of America

List of symbols

β	Orientation
°C	Celsius (degree)
a	Major axis
b	Minor axis
c	Centroid
cm	Centimetre
h	Hour
kg	Kilogram
l	Length
m	Meter
m^2	Squared meters
min	Minute
P	Perimeter
s	Second
t	Time

1. Introduction

Livestock production is the largest user of land in the world for grazing and production of feed grains and agricultural products. The global demand for livestock products is expected to further increase due to population growth, rising incomes and urbanization (Bruinsma, 2003). Increase in market demand for meat and milk products, to provide food for a growing population, has led to a rapid growth in the scale of cattle and pig enterprises globally. For example, by 2014 the global numbers of live cattle and pigs had reached 1475 and 986 million heads, respectively (Table 1.1). With an increase of 10.8 % in the global human population in the last decade, there has been a significant increase in pig and cattle meat production (around 32.6% and 9.2% growth, respectively). As the scale of animal husbandry around the world increases, addressing the issue of animal welfare becomes more essential.

Table 1.1- Changes in the global human population, cattle and pig inventories and production between 2005 and 2014 (faostat.fao.org).

	2005	2014	Growth (%)
Human population (billion)	6.5	7.2	10.8
Live cattle (million)	1387.5	1474.5	6.3
Live pigs (million)	883.8	985.7	11.5
Cattle meat (thousand tonnes)	59245.8	64681.1	9.2
Pig meat (thousand tonnes)	94352	115313.7	32.6
Cow fresh milk (thousand tonnes)	543444.2	655957.9	20.7

The relationship that people have with animals, and the duty they have to ensure that the animals under their care are treated correctly, is fundamental to animal welfare. Livestock welfare can be defined using such parameters as their behaviour, physiology, clinical state and performance (Averós et al., 2010; Costa et al., 2014; Nasirahmadi et al., 2015). There are many links between animal behaviour, health, emotions and welfare, and identification of appropriate behaviours helps to deliver better health, welfare and production efficiency (Nasirahmadi et al., 2017b). Behaviour plays an essential role in transmission of disease, and veterinarians use changes in animal behaviour for diagnosis of disease in some cases (Broom, 2006). For instance, a cow with lameness may arch its back and has abnormal walking. It is believed that emotions evolved to reinforce performance of behaviours important for survival, such as obtaining food and avoiding danger. In pigs, for example, hunger plays an essential role in their motivation for directing exploratory behaviour (Murphy et al., 2014).

Consumers and the wider society are increasingly concerned about the welfare, health and living conditions of farm animals. Awareness of animal needs underpins new production standards for animal health and welfare. Animals need to access fresh water and correctly formulated diets, which ensure gaining sufficient live weight and promote good animal health (Petherick, 2005). The appropriate environmental conditions lead to good animal welfare. High or low ambient temperatures, ventilation rate, and humidity are examples of environmental factors that may affect animal welfare. Animals also need proper facilities (e.g. space, housing, handling) to express normal behaviour without fear and distress. Early and real-time detection of normal and abnormal behaviours of animals reduces the cost of animal production, limiting losses from diseases and mortality, and improves the job satisfaction of the owners. However, due to the current scale of production, there is increasing awareness that the monitoring of animals can no longer be done by farmers in the traditional way and requires the adoption of new digital technologies.

The advancement of knowledge and technology in the current century, along with human expectations for adequate and high-quality livestock products, has therefore enhanced the need for improved production monitoring. Pig and cattle behaviour can provide information about their barn environmental situation, food and water adequacy, health, welfare and production efficiency. Real-time scoring of livestock behaviours is challenging, but the increasing availability and sophistication of technology make automated monitoring of animal behaviour practicable. With the development of new technologies, the application and integration of new sensors and interpretation of data from multiple systems with reducing processing times means that information supply for farmers and researchers has become easier (Barkema et al., 2015). There are many studies in the literature that demonstrate how such technologies can help in observation of both normal and abnormal behaviours of animals. Examples include studies based on Radio Frequency Identification (RFID), which is a wireless system included two parts: a data-carrying device (tags) and readers. In RFID, data are transferred by means of magnetic fields between tag and reader (Maselyne et al., 2014). The reader is a device with antennae to emit radio waves and receive signals from the tag. The tag uses radio waves to communicate its identity and other information to the readers. RFID have been used for locating animals, for detection of feeding and/or drinking behaviours of cattle (Sowell et al., 1998; Quimby et al., 2001; Wolfger et al., 2015; Shane et al., 2016) and pigs (Reiners et al., 2009; Brown-Brandl et al., 2013a; Brown-Brandl et al., 2013b; Andersen et al., 2014; Maselyne et al., 2014; Gertheiss et al., 2015).

There are many studies in the literature of methods by which technology and sensors help in observation of both normal and abnormal behaviours of animals, namely drinking, feeding, lying, locomotion, aggressive and reproductive behaviours. Further examples of the application of new technology are activity and lying behaviour monitoring in cattle and pigs using acceleration sensors attached to the animals (Robert et al., 2009; Trénel et al., 2009; Ringgenberg et al., 2010; Jónsson et al., 2011). An accelerometer is an electromechanical device that measures the acceleration of both static and dynamic forces. This technique has been widely applied for locomotion and lameness assessment (e.g. Nielsen et al., 2010; Grégoire et al., 2013; Conte et al., 2014; Van Nuffel et al., 2015), as has the use of other sensors which have been reviewed by Schlageter-Tello et al. (2014) for cows and Nalon et al. (2013) for pigs. However, attachment of sensors to monitor animal behaviours may cause stress and, in some cases, is impractical to use for scoring group behaviours due to their cost and vulnerability. One of the other technologies which has been used for a wide variety of applications in agriculture, industry, food engineering and animal science is the machine vision technique, which can provide an automated, non-contact, non-stress and cost-effective way to achieve animal behaviour monitoring requirements (Shao and Xin, 2008; Costa et al., 2014; Nasirahmadi et al., 2016b; Oczak et al., 2016).

In conclusion, to address the growing demand for meat and milk products, livestock farming has been scaling up during the last two decades. This gives new challenges in optimising the management of animal farming, which can be helped by the automated monitoring of farm processes (Banhazi et al., 2012). Automatic computer imaging systems could help both farmers and researchers to address the problems of monitoring animals, e.g. for visual scoring, animal weighing and other routine tasks which are both time-consuming and costly, and could result in more objective measurements by means of image processing techniques. A machine vision approach is a cheap, easy, non-stressful and non-invasive method which can be adapted to different animals, in both indoor and outdoor situations, using the animals' natural features (e.g. shape, colour, movement) for monitoring their behaviours.

2. Objectives of the research

For many years, human observations of animals have been carried out to assess their behaviour, health and welfare. The main problem with this approach is the high requirement for both time and cost for complete monitoring of the farm. This is most challenging in large-scale farms with a high number of animals.

The overall objective of this study is to develop an automatic, computer-based monitoring system for behaviour of group-housed pigs. The specific objectives include:

1. Developing automatic machine vision based detection for lying behaviour of pigs in groups.
2. Defining and categorising the group lying patterns of pigs.
3. Automatic assessment of lying pattern changes of pigs after enrichment substrate provision.
4. Developing an automatic computer-based detection system for mounting behaviour in pigs.

The research is presented in the form of state of the art image processing and neural networks algorithm development, farm experiments and application of the algorithms in the commercial farm situation. To date, no automatic lying behaviour detection system, along with different mathematical descriptions of group lying patterns in different ambient temperatures, or automatic mounting behaviour detection systems have been presented. To achieve this, different image processing algorithms in MATLAB® were developed to monitor pig behaviours captured from Closed Circuit Television (CCTV) cameras.

The present thesis, relating to the development of an automatic machine vision system for monitoring behaviours of pig groups, is structured in 8 sections. Section 3 and its sub-sections provide a review of literature on different types of camera and imaging systems used in livestock monitoring, the use of image processing for individual physical characterization of cattle and pigs and the monitoring of behaviours which may happen within the group. Section 4 covers material and methods for this research. Section 5 and 6 present results and discussion of the experimental components, along with an overall discussion of the research, while section 7 highlights future research needs. Summaries of the research in English and in German are given in section 8 and 9. Finally, references are presented in section 10.

3. Literature review

3.1. Imaging systems for livestock monitoring

Image acquisition, which is the first step of any machine vision system, is defined as transfer of the signals from a sensing device (i.e. camera) into a numeric form. Cameras are a crucial element in machine vision applications, however each type of camera offers different information on parameters of the image. The cameras applied in cattle and pig behaviour detection can be divided into Charge Coupled Device (CCD), infrared (IR) and depth sensor cameras.

The CCD cameras create images in two dimensions and are sensitive to visible bands reflected from objects (Mendoza et al., 2006). These types of camera need an additional source of light to make the image visible and the machine vision system consists of single or multiple cameras, i.e. video surveillance cameras, capturing objects which are visible to a human. Examples of using this type of camera in livestock behaviour detection are Shao et al. (1998), Hu and Xin (2000), Porto et al. (2015), Nasirahmadi et al. (2016b). The captured images are potentially suitable for image processing algorithms to extract image features based on colour, shape and textural properties. CCD cameras have the ability to detect pixels of objects in red, green and blue (RGB) bands. Nowadays, different image processing algorithms help to convert these bands to grey, hue, saturation, intensity and other parameters.

Infrared or thermal cameras work similarly to optical or common CCD cameras, in that a lens focuses energy onto an array of receptors to produce an image. By receiving and measuring infrared radiation from the surface of an object, the camera captures information on the heat that the object is emitting and then converts this to a radiant temperature reading (James et al., 2014; Matzner et al., 2015). Thus, while CCD cameras measure the radiation of visible bands, thermal cameras detect the characteristic near-infrared radiation (typically wavelengths of 8–12 µm) of objects (McCafferty et al., 2011). Thermal imaging was developed for industrial, medical and military applications, but it has also been applied in many livestock production studies as reviewed by Eddy et al. (2001), Gauthreaux and Livingston (2006), McCafferty (2007), McCafferty et al. (2011). All live animals emit infrared radiation, and the higher the temperature of an object, the greater the intensity of emitted radiation and thus the brighter the resulting image (Kastberger and Stachl 2003; Hristov et al., 2008).

In the last decade, the number of applications related to Three Dimensional (3D) imaging systems in machine vision has been growing rapidly, thanks to improved technology and reducing cost. The use of this type of imaging system in agricultural products has been recently described (Vázquez-Arellano et al., 2016). Depth imaging is a core component of many machine vision systems and, within this technology, time of flight (TOF) and Kinect cameras have been used widely in livestock applications. TOF cameras sense depth by emitting a pulse and then measuring the time differential for that emitted light to travel to an object and back to a detector. They can provide a 3D image using an infrared light source and CCD detector (Kolb et al., 2010; Pycinski et al., 2016) and the camera lens gathers the reflected light and images it onto the sensor or focal plane (Figure 3.1).

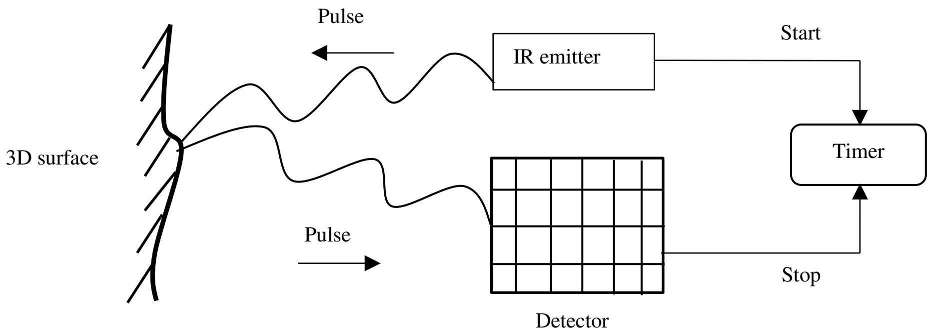


Figure 3.1- Time-of-flight (TOF) phase measurement principle.

The 3D depth sensing makes it possible to overcome common issues causing problems with Two Dimensional (2D) imaging systems, such as background removal, segmentation, feature extraction and sensitivity to lighting variance. TOF systems are limited by the number of data points that they capture at a given time and their relatively limited field of view. Therefore, TOF systems can lead to accuracy errors (Shelley, 2013). Although it is much easier and cheaper to use the 3D camera approach in farm environments rather than stereo vision, Laser or 2D triangulation, which are common alternatives for 3D reconstruction, the depth images still require some processing work to remove unwanted objects (e.g. noise, background), and in some cases calibration to deliver better results is needed. The Kinect sensor, introduced in 2010 and based on the TOF principle, made it possible for software developers to acquire a skeletal model of the user in real-time with no calibration needed (Han et al., 2013). The Kinect sensor lets the machine sense the third dimension (depth) of the object and the environment by employing data from a RGB camera, an infrared projector and infrared camera making the task much easier (Han et al., 2013; Nathan et al.,2015; Westlund et al., 2015; Marinello et al., 2015).

Once the basic images have been captured from these different camera systems, they are transferred onto a computer and are converted to digital images. The image processing technique enhances the quality of images by eliminating defects such as geometric complexity, inappropriate focus, repetitious noise, non-uniform illumination and camera motions or by the improvement of important features of interest (Narendra and Hareesh, 2010).

3.2. Image processing techniques used for characterising individual livestock

Although livestock usually live in groups, monitoring of individual animals is one of the main goals of researchers. Most individual studies on cattle and pigs have been concerned with inspection of their weight and body condition as well as measurement of their health and sickness characteristics, such as mastitis in cows. Some of the characteristics are expressed in the form of individual animal monitoring indices, which will be addressed in the following paragraphs along with their image analysis strategies applied.

3.2.1. Live weight

Knowledge of the live weight of pigs plays an important role in the control of performance-related parameters which affect the output of the herd, i.e. animal growth, uniformity, feed conversion efficiency, space allowance, health and readiness for market (Schofield, 1990; Brandl and Jorgensen, 1996; Wang et al., 2008; Kongsro, 2014). An individual pig's live weight is usually obtained using manual or automatic weighing scales, to which pigs are driven in a way which is laborious and stressful to both the animal and the workers (Wang et al., 2008; Kongsro, 2014), while automatic scales are usually costly devices (Kongsro, 2014).

Information extracted from the literature shows a range of different image processing methods for monitoring pigs' live weight. Based on length and width dimensions of pigs (i.e. length from scapula to snout, length from tail to scapula, shoulder width, breadth at middle and breadth at back) and boundary area, some researchers (Schofield, 1990; Brandl and Jorgensen, 1996; Schofield et al., 1999; Doeschl-Wilson et al., 2004) have used top view CCD cameras to obtain estimates of individual pig live weight. Live weight has also been estimated by means of a top view image with extracted features including area, convex area, perimeter, eccentricity, major and minor axis length and boundary detection, along with Artificial Neural Network (ANN) methods (Wang et al., 2008; Wongsriworaphon et al., 2015). Recently a fully automated weight estimation technique has been introduced to estimate a marked pig's weight individually (Kashiha et al., 2014b; Shi et al., 2016). Furthermore, approaches for pig live weight estimation by means of a Kinect camera have utilized infrared depth map images (Kongsro, 2014; Zhu et al., 2015).

Similarly, image processing has been used to measure cattle live weight due to the importance of live weight monitoring for milk and meat production, along with the difficulty of manually determining live weight on farm due to stress for the animals and their potential to cause damage to themselves, humans and weighing equipment. Tasdemir et al. (2011a and 2011b) and Ozkaya (2013) utilized top and side view cameras for cow live weight detection, using features like hip height, body length, hip width and chest depth extracted from images, along with multi-linear regression and fuzzy rule models. Previously, a thermography and image analysis based method was developed by Stajnko et al. (2008) for measurement of the live weight of individual bulls. The thermal camera was able to separate the bull from the surroundings accurately and the measurements were based on the tail root and front hoof templates on each image. Moreover, a TOF camera method has recently been applied for body weight detection of cows based on 3D body and contour features (Anglart, 2016).

3.2.2. Body shape and condition

Body shape and condition of a live pig/cow is an important indicator of its health, reproductive efficiency and value, whether for breeding or for carcass quality (Wu et al., 2004; Bercovich et al., 2013; Fischer et al., 2015). Assessment of live animal body condition by eye or hand is time and labour intensive and highly dependent on the subjective opinion of the stockman. However, imaging methods have become more affordable, precise and fast for on-farm application. Examples of using image processing for pig body condition have used 3D cameras for shape detection (Wu et al., 2004) and thermal cameras for shape and body contour detection (Liu and Zhu, 2013). Image processing has been widely utilized for assessment of cow body condition, based on anatomical points (points around hook and tail) detected with top view CCD cameras (Bewley et al., 2008; Azzaro et al., 2011) and thermal camera measurement has been used to assess the thickness of fat and muscle layers and provide a body condition score (BCS) (Halachmi et al., 2008; Halachmi et al., 2013). In other research, the angles and distances between 5 anatomical points of the cow's back and the Euclidean distances (Ed) from each point in the normalised tail-head contour to the shape centre were used for body shape scoring (Bercovich et al., 2013). Side view images have also been used for body shape capture of cows, based on RGB images and body features (González-Velasco et al., 2011; Hertem et al., 2013). In order to determine the 3D shape of a cow's body, TOF and Kinect cameras have more recently been utilized, based on extracting body features and/or back postures in 3D images (e.g. Weber et al., 2014; Salau et al., 2014; Fischer et al., 2015; Kuzuhara et al., 2015; Spoliansky et al., 2016).

3.2.3. Health and disease

Early detection of symptoms of illness or abnormal behaviour is essential to effectively deal with animal welfare and disease challenges in both cattle and pigs, and can help minimise lost production and even death of livestock. A method to detect the probability of a sick pig was tested by Zhu et al. (2009) by a combination of wireless technology and image processing. Monitoring of pigs daily movement, eating and drinking behaviours, along with wireless data, was considered as a tool for alarming suspected cases. The measurement of body temperature is a common method to monitor the health of an animal (Hoffmann et al., 2013). As a result, most of the research on health detection is based on surface temperature by using thermal cameras (e.g. Schaefer et al., 2004; Montanholi et al., 2008; Rainwater-Lovett et al., 2009; Wirthgen et al., 2011; Gloster et al., 2011; Hoffmann et al., 2013).

Mastitis, which is one of the most common diseases in dairy cows and causes major economic loss to dairy farmers, has been detected based on udder surface temperature measurement (Hovinen et al., 2008; Colak et al., 2008). Recently, a thermography method was also developed for automatic parasite counting on cattle bodies to improve their health and welfare. The difference in temperatures between ectoparasites, such as ticks and horn flies, and the cow's body temperature made it possible to detect these parasites in images (Cortivo et al., 2016). However, many external parameters (e.g. high or low temperatures, soiled surfaces and variable distance from object to lens), together with difficulties in interpretation of animal surface temperature, make the real-time monitoring of health and disease using thermography more challenging. As a result, in most of the studies other methods (e.g. clinical symptoms) have been investigated for their reliability in health problem detection.

3.2.4. Tracking

In order to automate monitoring of animals' health and welfare, tracking methods have been developed which differ according to the animal and husbandry situations. Livestock tracking tools which have been utilized can be listed as Bluetooth, WiFi networks, radio frequency methods and Global Positioning System (GPS) (Huhtala, 2007). However, the mentioned tools are more applicable to cattle rather than pigs. Pigs normally have more physical contact in pens and cannot easily carry electronic devices without risk of damage (Ahrendt et al., 2011). Furthermore, for large numbers of pigs many devices are needed which is not economically feasible. As a result, tracking animals by machine vision has many possible advantages in livestock monitoring.

McFarlane and Schofield (1995) applied a top view camera for tracking piglets, based on blob edge and an ellipse fitting technique, whereas Tillett et al. (1997) tracked individual pigs by using *x* and *y* coordinates of shape data of individual pigs over time sequences. Furthermore, movement of pigs in feeding stalls was investigated by Frost et al. (2000) by applying CCD cameras. Image processing approaches have been used for tracking the location of pigs in pens by Guo et al. (2015) and Nilsson et al. (2015). In another study, individual piglets were painted with different colours on their backs for tracking and the automatic algorithm was based on RGB value detection (Jover et al., 2009). In another study, a specific pattern was stamped on the back of each pig and ellipse fitting algorithms were employed to localise pigs in top view CCD images. Individual pigs were identified by their respective paint pattern using pattern recognition techniques (Kashiha et al., 2013b). A real-time machine vision system for tracking of pigs was developed by Ahrendt et al. (2011), based on building support maps and a Gaussian model of position and shape of individual pig.

In general, to improve animals' health, welfare and production efficiency, monitoring of individual animals plays an essential role in farm management. Measuring the individual weight, milk yield and lameness of dairy cows in robotic milking and using radio frequency methods of animal movement assessment for health detection are some examples of technology application. Image processing techniques for individual livestock monitoring seem promising due to drawbacks of alternative methods (e.g. price, stress of application and need for contact with the animal). The combination of imaging and sensor approaches could be more sensible in some cases. For instance the individual animal could be identified by using a sensor (i.e. RFID) while health parameters could be monitored by using image data. However, monitoring of some individual features (e.g. tracking) is still challenging, especially for animals in a herd, and the image processing methods need more investigation to address issues in commercial applications.

Information from the literature indicates various uses of image analysis methods in cattle and pig husbandry. Other than behaviour detection, which will be addressed later in this review, examples include teat position detection in robotic milking for dairy cows, based on colour and morphology features (Bull et al., 1996; Zwertvaegher et al., 2011) and milk yield estimation based on rear view depth, width and area of udder (Ozkaya, 2015). Furthermore, heat tolerance in pigs, based on surface temperature of group housed pigs, has been monitored (Brown-Brandl et al., 2013a; Brown-Brandl et al., 2013b; Cook et al., 2015).

The validation scales used for evaluating the machine vision detection technique and the performance of a behaviour detection system can be described as sensitivity, specificity, error rate, precision and accuracy (Grzesiak et al., 2010; Pourreza et al.,

2012) (Table 3.1). All accuracy results reported here are based on correlation to ground truth. Ground truth is used in machine vision to refer to data provided by direct observation (manual scoring) in comparison to the information provided by image processing.

Table 3.1- Validation criteria for machine vision techniques.

Performance criterion	Equation for calculation	
Sensitivity (%)	$\frac{TP}{TP+FN}$	TP= true positive (correct detection of a relevant behaviour)
Specificity (%)	$\frac{TN}{TN+FP}$	TN= true negative (correct detection of a not relevant behaviour)
Accuracy (%)	$\frac{TP+TN}{TP+FP+TN+FN}$	FP= false positive (incorrect detection a relevant behaviour)
Error rate (%)	$\frac{FP}{TP+FP}$	FN= false negative (incorrect detection of a not relevant behaviour)
Precision (%)	$\frac{TP}{TP+FP}$	

In the current section, the individual characterisation of cattle and pigs by image processing techniques has been reviewed. The detection of behaviours which may occur within the group will be addressed in the following sections.

3.3. Image processing techniques used for characterising grouped livestock

3.3.1. Feeding and drinking behaviour

Feeding and drinking behaviours are often thought to provide some indication of how much animals are eating or drinking and contain important information that can enable better management of animals and detection of problems (Botreau et al., 2007; Chapinal et al., 2007; Brown-Brandl et al., 2013a; Brown-Brandl et al., 2013b). Detecting these behaviours is therefore important in animal husbandry from an economic and welfare point of view and plays an essential role in meat and milk production. The amount of feed intake and water usage of dairy cattle affects milking efficiency (Azizi et al., 2009; Appuhamy et al., 2016) and changes in feeding and drinking behaviours in pigs could reflect pig health (Maselyne et al., 2016).

Traditionally, feeding behaviour has been monitored through direct human observation or using time-lapse video recording techniques (Bach et al., 2004; Meiszberg et al., 2009), but computer controlled feeding stations are now used to register the feeding or drinking behaviours of individual animals using electronic tagging methods, i.e. radio frequency (Rushen et al., 2012).

Recently, machine vision has been used for feeding and drinking behaviour detection in cattle and pigs. In order to register the presence of dairy cows in a feeding area and detect feeding behaviour, a multi-camera video system for obtaining top view images has been applied (Porto et al., 2012; Porto et al., 2015), and a classifier based on the Viola–Jones algorithm (Viola and Jones, 2004) by using shapes composed of adjacent rectangles (Haar-like features, which is a digital image feature for object recognition based on the difference of the sum of pixels of areas inside the rectangles) features has been developed. An image which contained the object (here cow) was considered as a positive image, whereas a negative one contained only the part of the object which made up the background of the image and did not contain the target object (cow). The ability of the system to detect cow feeding behaviour was reported to have a sensitivity of 87% when compared to visual recognition.

In another study, a feed intake monitoring system that quantified how much feed was distributed to, and consumed by, an individual cow was developed by Shelley (2013). A 3D imaging system was implemented to record and monitor the change in feed bins before and after feeding. The monitoring equipment measured feed intake by the change in volume by recording the 3D image before and after a cow had consumed its individual daily feed. The imaging system was placed inside an enclosed box to give consistent lighting. By using shape and contour data of feed in the bin, the volumetric amount of feed was determined. Once the correlation between feed volume and image data was obtained, the process moved forward to determine an output value (weight) for the bin of feed, using a linear mapping of volume to weight by means of linear regression to derive a single weight-based value of feed.

In order to automatically recognise feeding and drinking behaviours of lactating sows, a depth imaging system (Kinect) was developed by Lao et al. (2016). In this method, after removing unwanted objects like feeder and frame pipes, small holes from the subtraction in depth images were filled and, by converting the depth image to a binary image, the sow's physical features including the *x-y* centroid coordinates, head and hip pixels (leftmost and rightmost pixels, respectively) were identified.

Then, these features in the depth image of the sow were utilized for dividing the body into 7 body parts, namely; all, upper half, lower half, head, shoulder, loin and hip. Drinking behaviour was determined by searching sow pixels connected or near to the nipple drinker in horizontal distribution and with a height greater than the height of the nipple. For feeding behaviour they used the same strategy, registering when the head was in the feeder with up and down movement. An accuracy of 97.4% in feeding and 92.7% in drinking behaviours was reported for the proposed method when compared to manual scoring.

Previously, a similar approach was recommended by Kashiha et al. (2013a) for automatic detection of pig water usage by means of a CCD top-view camera. The centroid of the pig's body binary image was obtained by analysis of the body contour profile, and the distances calculated between the centroid of body and head, tail and ears. Drinking was defined when a pig was in the drinking area and based on distances of less than 10 pixels between head, ears and drinking nipple which lasted for at least 2 s (Figure 3.2). Comparison of results from the developed method and the real amount of water usage indicated that the drinking behaviour was detected with an accuracy of 92%.

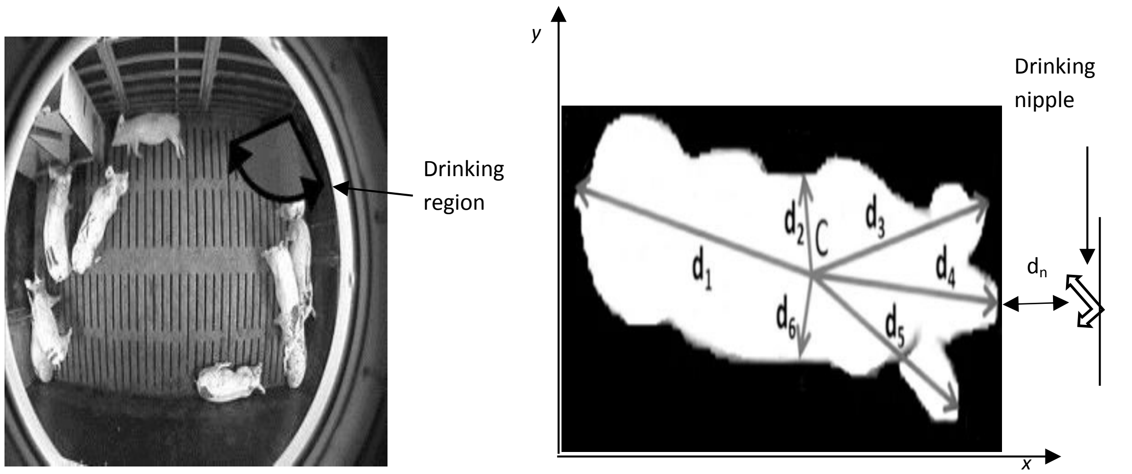


Figure 3.2- Possible drinking region (left), pigs body contour (right); centre (C), distance to tail (d_1), to sides (d_2 and d_6), to ears (d_3 and d_5), to head (d_4) along with distance to nipple drink (d_n). (Kashiha et al., 2013a).

In summary, to monitor feeding and drinking behaviours with image processing approaches, both 2D and 3D cameras have been utilized. Although, 2D monitoring is mainly based on shape and colour features of the animal, some classification models have been applied to enhance the process. However, the distance from object to camera is the main principle for 3D motion detection of animals. Identification of multiple animals during feeding and drinking times presents an additional challenge which is not completely addressed yet by the researchers in this field. Furthermore, no study was found based on automatic machine vision to label each animal for the usage of feed and water in both indoor and outdoor environments.

3.3.2. Locomotion and lameness behaviour

Animal locomotion is defined as the types of movements that an animal uses to travel from one place to another, and may lead to conclusions concerning welfare, health status, and behavioural disorders of animals (Brendle and Hoy, 2011). Manual locomotion scoring is a widely used method to detect lameness in cattle. This is done by visually inspecting a cow's standing posture or gait (Sprecher et al., 1997). Cows tend to exhibit gait abnormalities (or deviations from a healthy gait) as a reaction to pain or discomfort. Locomotion scoring is widely used for lameness detection in cows and abnormal locomotion considered as due to pain is based on the observation of cows standing and walking (gait), with special emphasis on their back posture (Van Nuffel et al., 2015). The use of sensors and different scoring methods for lameness behaviour detection has been reviewed (Rutten et al., 2013; Schlageter-Tello et al., 2014; Van Nuffel et al., 2015; Caja et al., 2016).

In order to automate cow lameness detection, different machine vision systems have been developed. An automatic system for continuous on-farm detection and prediction of lameness developed by Song et al. (2008) used a side view CCD camera. A background subtraction method was applied to the images and the centre points of the cow’s four hooves were separated and defined in different orientations (left fore, left hind, right fore, and right hind) based on the different distances between them in the image. By comparing the vertical values (y) with a pre-defined standard boundary value, and two horizontal values (x) on each body side, the fore hoof and hind hoof were labelled. The correlation between the hoof track way and visual locomotion scoring was obtained to check the accuracy of the method, and results showed a high average correlation coefficient (94.8%). The presented method was not able to distinguish small changes, i.e. Score 1 and Score 2. However, it showed a relatively higher success when a simplified scoring system was applied in their study. Large variations of overlap measurements for the same individual cow were reported (1 to 12 cm), even with constant gait score. Apart from the expected occlusions and camera protection problems, their results also indicated that changes in the step overlap were not consistently matched by changes in gait score. Step overlap is a variable that shows a relationship with manual gait scores, but it is not strong enough to be used as a single classifier for lameness in all cows. Later, in another approach for recording posture and movement of cows, a camera and pressure sensitive mat were used by Pluk et al. (2012) for recording posture and movement of cows. The exact timing and position of placement of the hoof on the ground was obtained from the pressure mat. Images from the camera, together with the position information, were used for image processing to automatically calculate the touch and release angles in the fetlock joint for the designated leg (Figure 3.3).

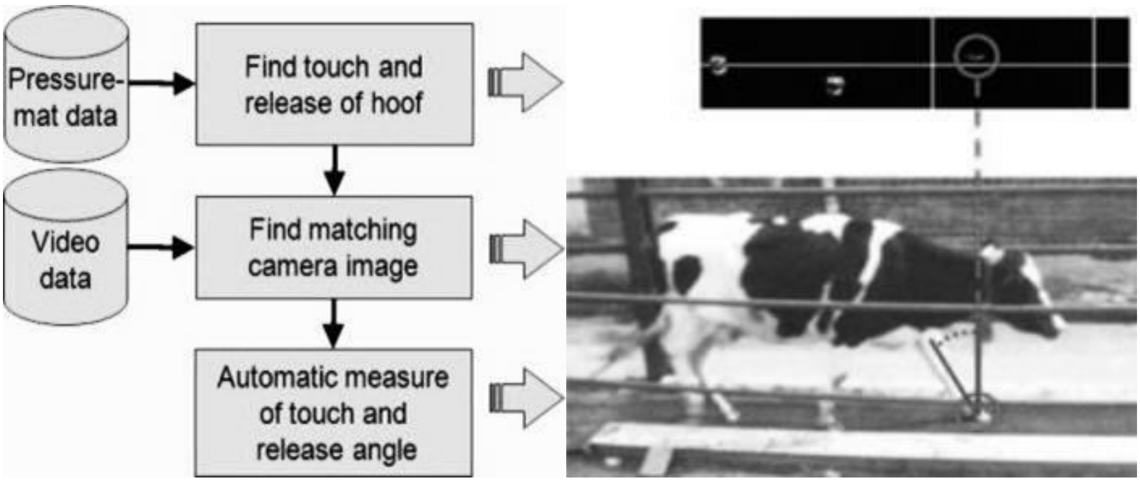


Figure 3.3- Combining pressure and image data for calculation of touch and release angles during cow locomotion (Pluk et al., 2012).

Their results indicated that, by detecting a decrease in the range of motion or an increase in the release angle of the front hooves, a large percentage of the cows could correctly be automatically detected for early lameness.

In order to extract back arch, as a postural indication of lameness, Poursaberi et al. (2010) applied circle fitting and standard background subtraction techniques along with statistical filtering to get a smoothed binary edge in images. Then, the back posture analysis was done by calculating the curvature of the back of each cow during standing and walking by fitting a circle through selected points on the spine line. The average inverse radius of arc was subsequently used for lameness scoring. The sensitivity, error rate, specificity and accuracy of the method were calculated as 100, 5.26, 97.6 and 94.7 % respectively. Similarly, lameness in cows was detected by side view CCD camera by Viazzi et al. (2013), who used back posture with an acceptable classification rate (more than 85%). The highest point in the curvature of the animal’s back was used as a starting point to find the body movement pattern. Two ellipses were fitted to the left (illustrates the shape of the back around the hip) and right (showing the shape of the back around the shoulder) sides of the highest point, and their orientations were obtained. Then, the intersection point of the two lateral axes of both ellipses, vertical distances between the highest point in the curvature and intersection point, the position of the muzzle, vertical distance between the muzzle and longitudinal axis of the right ellipse were used for calculation of body movement pattern.

In further research by this group (Viazzi et al., 2014a), a 2D (CCD) and a Kinect depth sensor were used to measure back posture for abnormal locomotion or lameness detection. The algorithm used for the 2D camera was based on back posture recognition (Poursaberi et al., 2010; Viazzi et al., 2013), while for the 3D image processing approach, each cow was entered separately to the recording area. Here, to separate two consecutive cows the minimal distance along the longitudinal direction was applied, when the Kinect depth sensor calculated distance between the cow and the sensor. Then, the contour of cow back and body orientation found in the 3D image was used for lameness detection. The contour of the cow was calculated and the distance between the symmetrical axes of the binary image was used to extract the head from the body of the cow. By detecting the peak of body, the back and neck of the cow were obtained in the image. The body orientation was calculated by using the body features and then the highest pixels around the orientation axes (10% of the cow width) represented the back spine. The highest point in the curvature of the animal's back was used for the starting point and then the same procedure as already discussed applied for body movement pattern calculation.

Recently, 3D depth video was applied in another study to detect early lameness in dairy cows (Abdul Jabbar et al., 2017). The captured top-down 3D image of the cow's body was used to segment high curvedness features of hook bones and the spine (Figure 3.4). Then, by tracking the segmented regions (hook bones and spine) a proxy of locomotion was introduced in the form of height measurements from the tracked regions. This proxy was further analysed in the form of gait asymmetry to assess the locomotion and detect early lameness. An accuracy of 95.7% with a 100% sensitivity (detecting lame cows) and 75% specificity (incorrectly detecting non-lame cows) was obtained using a Support Vector Machine (SVM) classifier.

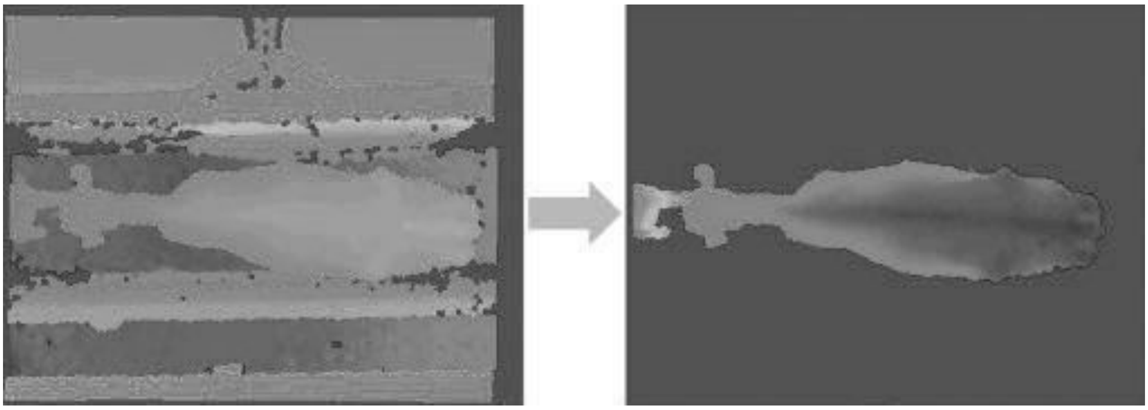


Figure 3.4- Example of depth image representation with a 3D camera: a raw depth cow image (left), the same image with the background removed (right) (Abdul Jabbar et al., 2017).

Monitoring of pigs' locomotion using different technologies can serve different purposes, i.e. detection of playing and lying behaviours (Kashiha et al., 2014a), lameness detection (Van Riet et al., 2013; Nalon et al., 2013) and welfare assessment (Lind et al., 2005). In order to use image processing to assess pig locomotion, a software tool was developed based on a combination of image subtraction and automatic threshold detection methods (Lind et al., 2005). The drawback for the proposed system was that pigs had to be manually controlled by allowing them to walk one by one in front of the camera. Kongsro (2013) developed an image processing technique using top view images for pig locomotion monitoring. The RGB images were cropped to focus on the significant areas of the image and then converted to grayscale. Background noise was filtered out by labelling of the biggest object after converting grey images to binary. A filter was designed to capture only pig cropped RGB images where the centre point was moving. The position of the head and ears of the pig was located using the width of the pig, and the positions were found using the derivative of the width curves. By finding the image map to represent total movement of the pig in a stack of added binary images, and based on the fact that the largest values would represent the pixels where the binary pig would appear most frequently, the locomotion of the pig was obtained in images. Background subtraction and ellipse fitting techniques for localising pigs in top view images, and calculating movements of ellipse features, made the tracking of locomotion of pigs more accurate (89.9%) (Kashiha et al., 2014a). The principal was based on the linear movement of the centre of the fitted ellipse in different time frames and the angular movement (orientation of ellipse) for tracking some marked pigs in images in a sequence of frames. Locomotion was defined as when a pig (centre of fitted ellipse) moved more than 40% of its body length (value in pixels). In order to make the technique independent of body size of the pig, the sum of linear and angular movements was divided by the length of each pig.

Locomotion of groups of pigs has been obtained by finding an activity index (Ott et al., 2014). Images of each top view CCD camera were analysed using background subtraction algorithms, then the images were binarised to eliminate the background and noisy areas were filtered out from the image by a morphological closing operator. Calculation of the activity index was based on the difference in pixel values between the binary image at time *t* and that at time *t+1*. A strong correlation was obtained between human observation, as an evaluation tool, and the proposed technique.

Pig group movement has also been investigated by means of the optical flow pattern (Gronskyte et al., 2015; Gronskyte et al., 2016). Optical flow is defined as the distribution of the apparent velocities of objects in an image, caused by the relative motion between camera and the object. The method was based on the analysis of motion and the estimation included optical flow estimation, identification of pigs, optical flow filtering and distortion correction, feature extraction, and frame classification. In order to determine optical flow a correction method (Horn-Schunck method) was applied. Thresholding of the pixel colour values was applied to pig movement monitoring, then to identify individual pigs colour map adjustment and filtering, blob detection, image dilation and hole filling were applied. SVM as a classifier was utilized to classify pigs' movement in different transportation and slaughterhouse situations. A 6.5% error rate was obtained from the model, however the sensitivity and specificity were high at 93.5% and 90%, respectively.

Locomotion behaviour has also been investigated using the Kinect depth camera system to detect pig lameness. Movement of pigs was first captured by using the Vicon 3D optoelectronic motion analysis system to detect the characteristic locomotory changes of lame pigs (Stavrakakis et al., 2015a). This system was then compared with the Kinect sensor to distinguish sound and lame pigs by Stavrakakis et al. (2015b). Hemispherical, reflective markers were attached at the central nasal bone, the mid-neck proximal to shoulders (frontal to the shoulder widening), the posterior mid-thorax, anterior mid-pelvis and tail base of pigs (Figure 3.5). A high correlation between Vicon marker trajectory data and the vertical excursions of the Kinect sensor on the neck marker was found for lame pigs.

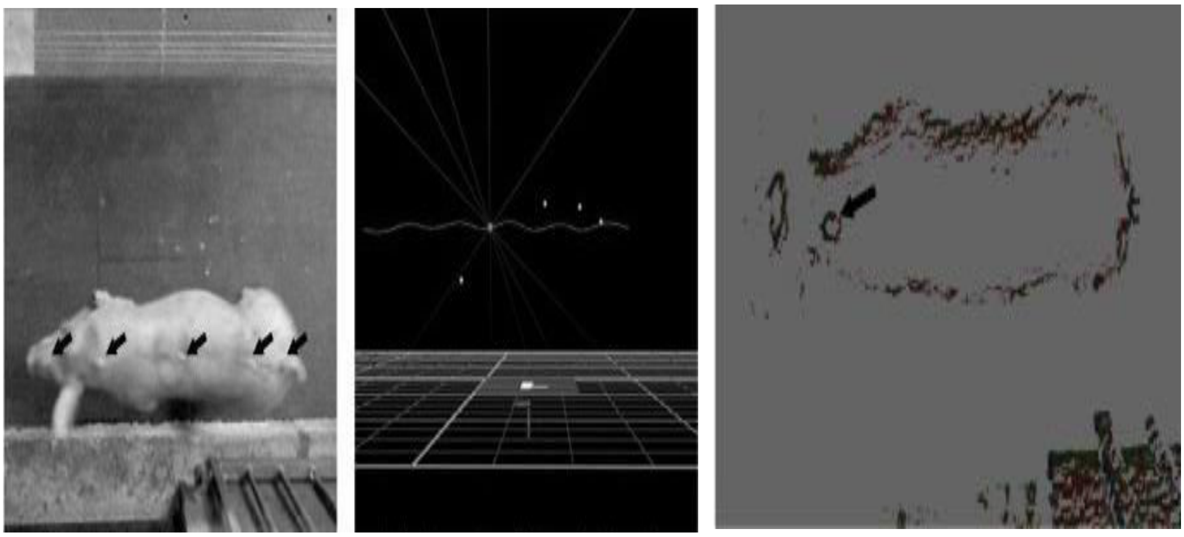


Figure 3.5- (left) five reflective Vicon markers, (middle) reflective marker visible on the Vicon software, (right) neck marker extracted by Kinect (Stavrakakis et al., 2015b).

In all, different types of automatic locomotion and lameness behaviour detection have been developed. Lameness detection of cows by means of side view CCD camera has been adopted in several studies, mainly based on back posture/arc and gait asymmetry analysis. However, to have a better detection, a combination of 2D and 3D depth images has been applied in other studies. Monitoring of pigs' locomotion by machine vision techniques is still challenging, due to their similarity in shape and size, so using some mark or paint on a pig's body or using radio frequency tags could be an alternative for short time locomotion tracking. Locomotion behaviour characterisation for pain assessment in lame animals, especially in pigs, still needs further effort for earlier detection in terms of applying automatic machine vision approaches for welfare improvement.

3.3.3. Aggressive behaviour

Aggressive behaviour amongst animals includes behaviours that involve actual or potential harm to another animal. Most farm animals live in groups and aggressive behaviour can be observed in the first days after the mixing of unfamiliar animals, or when competition for resources occurs such as during feeding times. This behaviour can affect growth, health and welfare of animals and gives rise to economic loses from reduced performance. Most studies of aggression detect the behaviours using direct observation or video recording with subsequent human decoding. However, automatic monitoring of aggressive behaviours in livestock based on image processing has recently been developed. A continuous automated detection of aggressive behaviour among pigs by means of CCD image features has been developed (Viazzi et al., 2014b). Two features were extracted from the segmented region of the Motion History Image (MHI); i) the mean intensity of motion which represents how strong and intense the motion is in the image, and ii) the occupation index which illustrates the distribution of movement inside the regions. A Linear Discriminant Analysis (LDA) was used to classify aggressive interactions in every episode with an accuracy of 89.0%, sensitivity of 88.7% and specificity of 89.3%.

In another study, the feasibility of a method for aggressive behaviour detection based on a percentage of activity index (number of pixels of moving animals/total number of pixels) and ANN was tested (Oczak et al., 2014). Five features (average, maximum, minimum, sum and variance) of the activity index were calculated from the recorded videos (average, maximum, minimum, sum and variance) over different time intervals and classified high aggression events with a sensitivity of 96.1%, specificity of 94.2% and accuracy of 99.8%. The Kinect depth sensor has also most recently been utilised to recognise and classify aggressive behaviour among pigs with an accuracy of 95.7% and 90.2%, respectively (Lee et al., 2016). In their study, the automatic detection and recognition of pig aggression consists of three modules; the pre-processor, the feature generator, and the aggression detector and classifier. The depth information related to pigs is obtained using a Kinect depth sensor, then five features (minimum, maximum, average, standard deviation of velocity, and distance between the pigs) were extracted from the depth image. Finally, the aggression detector classified (using SVM) the features to detect the aggressive events, based on behavioural sub-types, i.e. chasing (following another pig with biting) and head-to-head/body knocking (hitting the snout against the head/body of another pig).

In addition, a CCD based method was applied to monitor interactions (i.e. body pushing, head butting, head pressing, body sniffing) between dairy cows (Guzhva et al., 2016). Geometric features (distances) were extracted from every pair of cows then the values used as inputs of a SVM classifier with a detection accuracy of around 85%. However, although the CCD and Kinect cameras have been applied to address aggressive behaviour detection in some studies, further efforts are needed in commercial conditions to develop a reliable alarm system for farmers.

In addition to the use of machine vision approaches to monitor the behaviours reviewed in the preceding sections, other behaviours of group housed animals have also been studied. Two of these, which are reviewed in the following sections, are the subject of the experimental work in this doctoral thesis.

3.3.4. Lying behaviour

Lying behaviour plays a critical role in livestock health and welfare. In dairy cattle, the lying behaviour affects the milk production, and deprivation of adequate lying time reduces welfare (Bewley et al., 2010). The duration and frequency of lying bouts are behavioural indicators of cow comfort, and adequate opportunity to rest and lie down are considered important for maximising meat and milk production (Porto et al., 2013; Haley et al., 2000).

In order to detect cows' lying behaviour in real time, a top view CCD camera system was developed (Cangar et al., 2008). The centre point and the orientation of cow were calculated in the first image and given to a lying detection algorithm. Lying and standing behaviours of a cow were classified as a function of time, based on the *x*–*y* coordinates of the geometric centre of the animal, back area of cow (m^2) and the cumulative distance walked. On average 85% of lying and standing behaviours were correctly classified. Porto et al. (2013) detected cow lying behaviour with a high sensitivity (92%) using CCD cameras based on Viola and Jones algorithm (Viola and Jones, 2004).

A multi-camera video recording system was installed to monitor a panoramic top-view, and positive and negative images were cropped from the panoramic top-view image of the barn. The positive and negative images were used for training a classifier based on the Viola-Jones algorithm, and then each trained classifier was tested in testing phase. Although the pixel brightness values of the image areas of the stalls were highly variable during the daylight hours, results indicated that images used for the training and execution of the lying behaviour detector did not require any image enhancement thanks to the classification method.

Pigs spend most of their time lying and, in some cases, older pigs lie for up to 90% of their daily time (Ekkel et al., 2003). Their lying behaviours can provide information on environmental factors affecting production efficiency, health and welfare. Temperature is the main parameter affecting pigs lying behaviour; at high environmental temperatures, pigs tend to lie down in a fully recumbent position with their limbs extended and avoid physical contact with others, while at low environmental temperatures, pigs will adopt a sternal lying posture and huddle together (Hillmann et al., 2004; Spoolder et al., 2012). Design of the pen, location of feeders and drinkers, air velocity and humidity are other factors which affect the lying behaviour (Spoolder et al., 2012; Costa et al., 2014).

Observations of the lying behaviour of pigs have already been made in numerous studies, often in conjunction with other behavioural and/or physiological features of the animals. However, these investigations have generally been carried out under experimental conditions, reflected by a small number of pigs in the pen.

The influence of floor and surface temperature on thermal behaviour of pigs was investigated by Geers et al. (1990). Experiments have been carried out to study the lying postures and space occupation (Ekkel et al., 2003; Spoolder et al., 2012), and to assess optimal temperature ranges for fattening pigs of different weights kept in pens (Hillmann et al., 2004). The results showed that with increasing temperature, pigs were more often lying in the dunging area and without contact with pen mates, whilst pigs showed huddling at lower temperatures. The same result was reported by Huynh et al. (2005) when investigating the effect of high temperature and humidity on the behaviour of growing pigs. Such data have generally been collected either by direct observation of the pen or with the aid of video recordings. These methods are both labour-intensive and time-consuming (Stukenborg et al., 2011).

Accelerometers as sensors have been also used for characterising changes in livestock postural behaviour mainly for cattle and sows, but some limitations (i.e. risk of destruction and price) make them almost infeasible for research on group-housed pigs.

There are several recent studies in the literature where computer vision has been applied to pig group behaviour (Ahrendt et al., 2011; Kashiha et al., 2013; Viazzi et al., 2014; Ott et al., 2014). Image processing features were used as inputs for environmental control in piglet houses by Wouters et al. (1990). Shao et al. (1998) used CCD cameras to obtain behavioural features from binary images of pigs, namely the Fourier transform, moments, perimeter and area, which were used as the input data to an ANN to identify pig lying behaviours. The highest rate of correct classification was obtained by combination of perimeter, area and moment. Subsequently, Shao and Xin (2008) used other features, i.e. object compactness, average frequency of pixel change from background to foreground, area occupation ratio, and moment invariant, to detect and classify lying behaviours of grouped pigs. The developed machine vision system could successfully detect motion of the pigs, segment the pigs from their background, and classify the thermal comfort state of the pigs. More recently, other studies have been carried out using imaging systems to study lying behaviours of grouped pigs in different environmental situations.

A research group has performed image processing in pigs focusing on behaviour classification (Costa et al., 2013). The aim of this study was to develop an innovative method for measuring the activity level of pigs in a barn in real time. An infrared-sensitive camera was placed over two pens of the piggery, images were recorded for 24 h a day for eight days during the fattening period, and the activity and occupation indices were calculated every second in real time. In a similar study, Costa et al. (2014) used infrared sensitive CCD cameras for detection of pig behaviours, including lying, in different conditions of ventilation rate, air speed, temperature and humidity. The difference between the pixel intensity value of an image and the previous image was taken and, from this difference, the binary activity image was calculated by setting all pixels between thresholds to 1 and others to 0.

Although these studies have concentrated on describing activity and resting parameters by image analysis, no specific patterns of change in lying behaviour in different environmental circumstances have been investigated in groups of pigs under commercial farm conditions. There are different contexts in which knowledge of lying behaviour of group-housed pigs could be useful to farmers and researchers. Two of these are reviewed below; the first relates to the possibility to automatically monitor pig thermal comfort, while the second relates to understanding how pen design and management will impact on pig use of different functional areas within the pen.

3.3.5. Categorizing pig lying behaviour in relation to the thermal environment

The heat regulation capacity of pigs is poorly developed compared to other mammals and heat loss is critical for them (Mendes et al., 2013). Controlling environmental parameters helps to deliver high health, welfare and production performance efficiency (Mount, 1968; Shao et al., 1998). The activity, feed intake and lying behaviour of pigs will change in different thermal conditions (Hillmann et al., 2004; Renaudeau et al., 2008; Spoolder et al., 2012; Weller et al., 2013). When the temperature drops, pigs try to increase their heat production by means of energetically demanding muscular shivering thermogenesis and they try to reduce their heat loss by social and individual thermoregulatory behaviours. Therefore, by investigation of pig lying posture and group lying pattern, it could be possible to assess how comfortable or uncomfortable they are in their current environment. This requires a method to further process and interpret information from the images which are captured.

ANN is a non-linear modelling technique which can provide the classification abilities and processing information into the area of human brain level of performance. The ANN has recently been of interest to researchers and engineers in various research areas and industries. The ANN is increasingly being applied to the dynamic modelling of process operations, pattern recognition, process prediction, optimizing, non-linear transformation, remote sensing technology and parameter estimation for the design of controllers (Nasirahmadi et al., 2014; Oczak et al., 2014).

The ANN model contains an input layer, an output layer and one or more hidden layers. The number of neurons in the input is equal to the number of system inputs and output layer is equal system’s outputs. The neurons of the input layer are connected with the first hidden layer of the network, the first and last hidden layer of the network are connected to second and the output layer of the network, respectively (Oczak et al., 2014).

Some of the ANN applications in recent years have been in livestock based research: dairy cattle (Grzesiak et al., 2010), sheep (Kominakis et al., 2002; Tahmoorespur and Ahmadi, 2012) and pigs (Oczak et al., 2014; Wongsriworaphon et al., 2015). The performance of classifiers has a significant effect on machine vision outputs (Pourreza et al., 2012), and the feed-forward neural network is one of the most powerful classifiers, which could be fast enough and acceptable for many processes (Khoramshahi et al., 2014). The Multilayer Perceptron (MLP) network has become very popular as a feed-forward network architecture; the complexity of the MLP network depends on the number of layers and neurons in each one (Chandraratne et al., 2007).

The frequent fluctuations in external air temperature in the UK make barn ventilation management difficult. Room temperature in a building for growing pigs is normally kept within their thermal comfort zone (at around 20 ^{o}C), and the conventional measuring systems in commercial pig farms are based on only one or two air temperature sensors at fixed points above pig level (Mendes et al., 2013). This system cannot respond quickly to climate changes in farms, so finding a method which indicates the thermal experience of the pigs themselves by image processing could be a first step to improve control of the ventilation system for better thermal comfort and welfare of pigs in the room.

3.3.6. Categorizing pig lying behaviour in relation to use of functional areas in the pen

The natural behaviour of pigs is to establish separate function areas within their living space for behaviours such as feeding, resting, excreting and exploratory activity (Stolba and Wood-Gush, 1989). This is important to maintain hygiene and allow stable resting behaviour. Pigs are animals which are naturally motivated to root in their surroundings and, in natural conditions, spend a large part of their active time searching for food (Studnitz et al., 2007). Access to enrichment materials can improve pig welfare by reducing the level of aggression (Day et al., 2002) and the biting of tails, ears and other body parts (Van de Weerd et al., 2006; Zonderland et al., 2008; Jensen and Pedersen, 2010), and allowing the animals to express behavioural elements such as feeding and exploring (Bracke et al., 2007; Vanheukelom et al., 2012).

European legislation states that pigs must have permanent access to sufficient quantity of material to enable manipulation behaviours (Commission Directive, 2008/120/EC). Observations of the use of different enrichment materials for pigs have already been made in numerous studies. It has been shown that substrates in which pigs can root are more attractive than hanging toys (Scott et al., 2006). Furthermore, use of a rooting substrate can be influenced by its complexity and accessibility. For example, Jensen and Pedersen (2007) demonstrated that pigs prefer more complex rooting materials and valued maize silage mixed with chopped straw about 4 times more than chopped straw. In a subsequent study (Jensen and Pedersen, 2010) they confirmed this preference and showed that reducing the number of pigs increased the manipulation of rooting material. The nutritional properties of rooting material can also influence behaviour. Bolhuis et al. (2010) investigated the effect of fermentable starch in barren and enriched pens with straw bedding on lying, activity and aggression of pigs. The enriched pens increased activity, exploration and play behaviour while declined manipulation of pen mates.

In terms of providing enough materials and space for pigs, limited accessibility of rooting materials may lead to aggression and restlessness by causing competition in groups of pigs (Van de Weerd et al., 2006). Therefore, pigs should have enough material and space to allow several pigs to explore and manipulate the material simultaneously (Zwicker et al., 2012).

This suggests that distribution onto the flooring would be preferable to a localised substrate dispenser. Whilst it has been demonstrated that the provision of a rooting material is desirable to meet behavioural needs, in pens with solid or partly slatted flooring enrichment substrates are often placed into the lying area to avoid contamination or passage into the slurry system. However, the provision of enrichment material generally increases activity (e.g. Lyons et al 1995) and this might be deleterious if resting is disrupted in this area of the pen.

Studies on the effect of enrichment provision have generally been done by video recording and subsequent human quantification of behaviours, which is both a labour-intensive and time-consuming method. Image processing therefore offers an automated methodology to assist researchers in studying the influence of pen design and management, such as method of enrichment provision, on the establishment and maintenance of functional areas by groups of pigs.

3.3.7. Mounting/Reproductive behaviour

Detecting reproductive behaviour in cows and sows is very important for breeding management, as the estrous cycles occur only periodically and correctly detecting the signs of estrus is very important for reproductive success and economic efficiency of a herd (Tsai and Huang, 2014). Mounting behaviour, defined as when an animal lifts its two front legs and puts these or its sternum on any part of the body or head of another animal, is the most widely used indicator of reproductive behaviour for estrus detection (Rydhmer et al., 2006).

In order to detect mounting among dairy cows, a top view machine vision system was developed by Tsai and Huang (2014). In a mounting event, initially one cow closely follows another cow for a few seconds, so the following and mounting behaviours were identified based on the changes of moving object lengths in binary images in sequential frames. The following behaviour yields a moving object with the length of approximately 2-cows in images. The length of the moving object in images will then be changed to roughly 1.5 cows while they are performing the mounting behaviour. Finally, an operator (farmer) is required to view the recorded video frames to confirm that the detected results are true estrus/mounting events.

Both male and female growing pigs also perform mounting events, with different frequencies (Rydhmer et al., 2006; Hemsworth and Tilbrook, 2007). Mounting behaviour amongst pigs can increase the risk of injuries, such as bruises and damage to the skin when pigs mount one another and scratch the back with the claws of the forelimbs (Faucitano, 2001; Harley et al., 2014), and lameness or leg fractures (Rydhmer et al., 2004). These injuries and the general unrest in the group can have considerable negative economic consequences (Rydhmer et al., 2006). Although the level of activity declines with increasing weight, mounting behaviour (Thomsen et al., 2012), and skin lesions and lameness (Teixeira and Boyle, 2014), happen during the entire growing period of pigs.

Investigations of the mounting behaviour of pigs have already been made in different studies. However, these have generally been carried out using direct visual observations to sample behaviour under experimental conditions, reflected by a small number of pigs in the pen. Hintze et al. (2013) developed an ethogram of different types of mounting behaviours and their consequences. According to their classification, sexual mounts were longer than non-sexual mounts and were associated with more screaming, which is an indicator of stress and reduced welfare in pigs, by the mounted animal.

Every year approximately 100 million male piglets are castrated in the European countries to control risk of boar taint and undesirable male behaviours. Surgical castration is a painful and stressful event (Prunier et al., 2006; Hintze et al., 2013), and its abolition is currently being proposed. If systems with entire male pigs are adopted in consequence, employing an automated machine vision method as a non-contact way for monitoring mounting behaviours in pig farms could help to inform farm managers about the number of mounting events and identify pens requiring intervention. It would also facilitate large-scale research into methods to reduce this behavioural problem.

In conclusion, image processing has been an important technique for a wide variety of applications in agriculture and food engineering. This technique is an alternative, cheap and non-contact method to replace human observation of behaviour and causes no disruption to the animals' normal behaviour (Tillet et al., 1997; Shao and Xin, 2008; Costa et al., 2013; Kashiha et al., 2014).

Having identified knowledge gaps in the literature, two aspects of the further implementation of image analysis in monitoring pig behaviour are addressed in this thesis. The main purpose of the first study was to identify the lying pattern of pigs, the location of pigs during lying time and the distance between them using image analysis technology based on a Delaunay Triangulation (DT) method involving CCD cameras. The DT model does not investigate in detail the mathematical relationships showing how pigs behave in different temperatures, so different lying patterns (close, normal and far) under commercial pig farm conditions were defined and computed using the mathematical features of their lying styles. Then, based on DT features and using a MLP network, lying patterns were classified in different thermal categories. To illustrate a practical application of the developed image processing algorithm, the change in lying position of pigs was investigated, based on an ellipse fitting method, in pens enriched by daily maize silage provision into the lying area compared with control pens which had only a suspended enrichment toy in the activity area. In the second study, an automatic image processing model was developed to monitor mounting events among group pigs under commercial pig farm conditions.

4. Material and methods

4.1. Animal and housing

The observations were conducted at a commercial pig farm in the UK (Figure 4.1). A series of rooms each housed 240 finishing pigs; rooms were 14.35 m wide × 18.60 m long, mechanically ventilated and subdivided into 12 pens, each 6.75 m wide × 3.10 m long, and with a fully slatted floor. All pens were equipped with a liquid feeding trough and one drinking nipple.

Figure 4.1- External view of the commercial barn (top) and internal view of a research room (bottom).

One room was selected for the work and the white fluorescent tube lights were switched on during day and night. Room temperature was recorded every 15 min over the total experimental period with 16 temperature sensors (TE sensor Solutions, 5K3A1 series 1 Thermistor, Measurement Specialties Inc. USA) arranged in a grid pattern.

The experimental phase started after placement of pigs of about 30 kg live weight in the pen. Each temperature sensor was positioned around 20 cm above the pen walls (suspended from the ceiling) which was the nearest possible distance to the pigs without risk of damage. All sensors were set up and calibrated specifically for the experiment and the average of all sensors was used for room temperature calculation. The camera (Sony RF2938, Board lens 3.6 mm, 90^{o}, Gyeonggi-do, South Korea) was located 4.5 m above the ground with its lens pointing downward and directly above each pen to get a top view (Figure 4.2). Cameras were connected via cables to a Personal Computer (PC) and video images from the cameras were recorded simultaneously for 24 h a day and stored on the hard disk of the PC using Geovision software (Geovision Inc.) with a frame rate of 30 frame per second (fps).

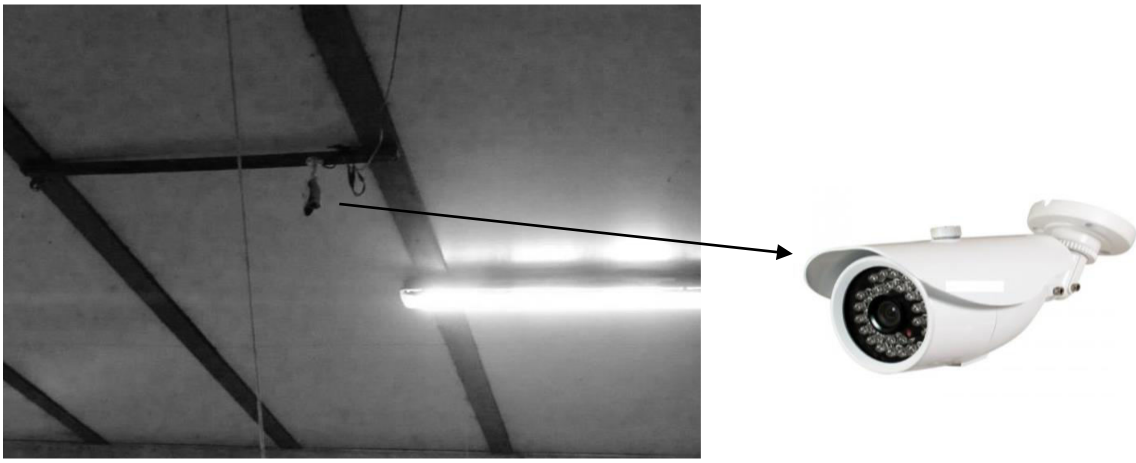


Figure 4.2- A camera and lighting source used in this study.

4.2. Image processing

The original resolution of an extracted image from the video was 640 × 480 pixels. In order to remove Barrel distortion in the images, camera calibration was carried out using the 'Camera Calibration Toolbox' of Matlab® (R2014b, the Mathworks Inc., Natick, MA, USA) and 25 images of a checkerboard pattern were taken in different orientations for each camera (Wang et al., 2007). Images from each camera were then analysed and, in order to extract foreground objects (pigs) from the background (pen), a background subtraction method was used. The threshold of grey image was determined based on Otsu's method, which chooses the threshold to minimize the intra-class variance of the black and white pixels (Otsu, 1979). Then the threshold was applied to convert the greyscale image into a binary [0, 1] image, and 1 assigned to the object and 0 assigned to the background. Erosion and dilation orders with disk structure were used for smoothing of edges. To remove small objects from the image, a morphological closing operator with a disk-shaped structuring element was used (Gonzalez and Woods, 2007) (Figure 4.3). Since each single pig in the image is similar to an ellipsoidal shape, the *x–y* coordinates of each binary image could be used for ellipse fitting algorithms to localize each pig. As a result, ellipse parameters such as "Major axis (a)", "Minor axis (b)", "Orientation (β)" and "Centroid (c)" could be calculated for all fitted ellipses to separate the touching pigs (Figure 4.4). Therefore each pig's body was extracted as an ellipse using the direct least squares ellipse fitting method and the aforementioned ellipse parameters (McFarlane and Schofield, 1995; O'Leary, 2004; Kashiha et al., 2013).

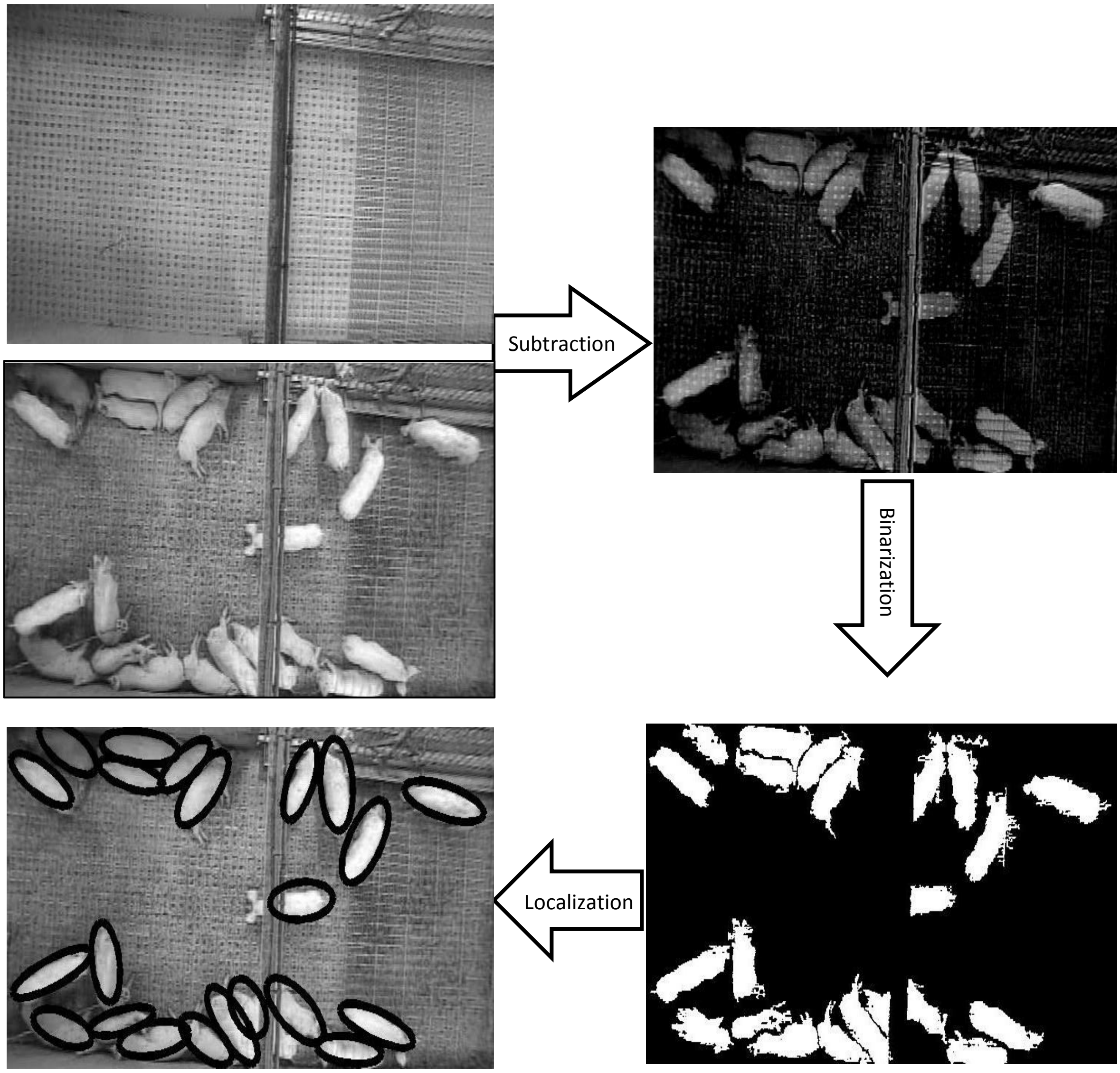


Figure 4.3- Image processing steps in this study; background (top left), grey image (middle left), subtracted image (top right), binary image (bottom right) and fitted ellipse (bottom left).

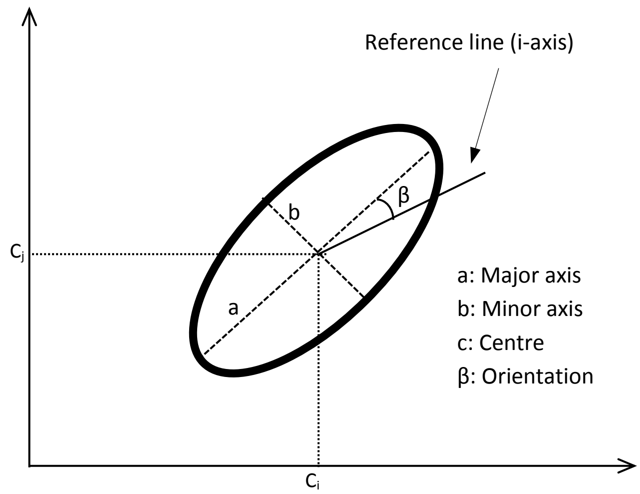


Figure 4.4- Ellipse parameters used in the ellipse fitting method applied to each pig.

4.3. Lying behaviour and position changes

In order to detect lying behaviour and position changes, two pens were selected for the experiments from the 12 pens in a room (Figure 4.5), each containing 22 pigs. To develop algorithms for continuous automated identification of changes in the lying pattern of the pigs, the location of each group of pigs needs to be known during defined periods. After downloading the recorded data, the video files were visually investigated and labelled (24 h/day for five days selected from the first 15 days) in order to evaluate animal lying times during the study. Four 30-min durations (duration 1, from 6.00 to 6:30 AM; duration 2, from 12.00 to12:30 PM; duration 3, from 18.00 to 18:30 PM; duration 4, from 0.00 to 0:30 AM) were selected based on observations that showed almost all pigs to be lying in these times during the 24 h in a day.

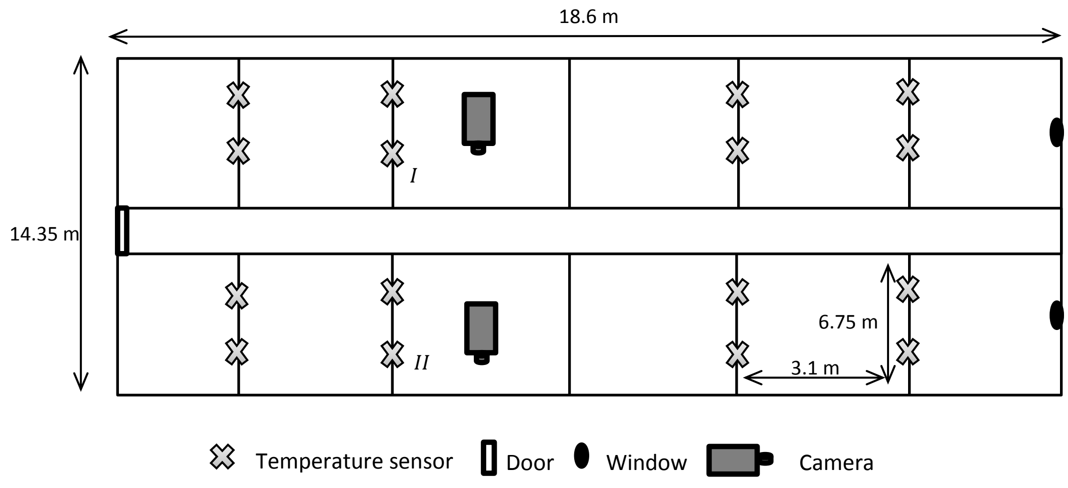


Figure 4.5- Top view of the research room and the two pens used for lying change studies.

Extracted images from video files were analysed according to the scheme presented in Figure 4.6 using the MATLAB® software. To describe the lying pattern of the pigs, a method using the DT was applied. The DT of a set of points on a plane is defined to be a triangulation such that the circumcircle of every triangle in the triangulation contains no point from the set in its interior and the circumcircle of a triangle is the unique circle that passes through all three of its vertices (Hansen et al., 2001). The DT maximized the minimum angle of all the angles of the triangles in the triangulation and tended to avoid skinny triangles. It is one of the most popular techniques for generation of unstructured meshes and the principle of this method was originally developed from the study of structures in computational geometry (Jin et al., 2006).

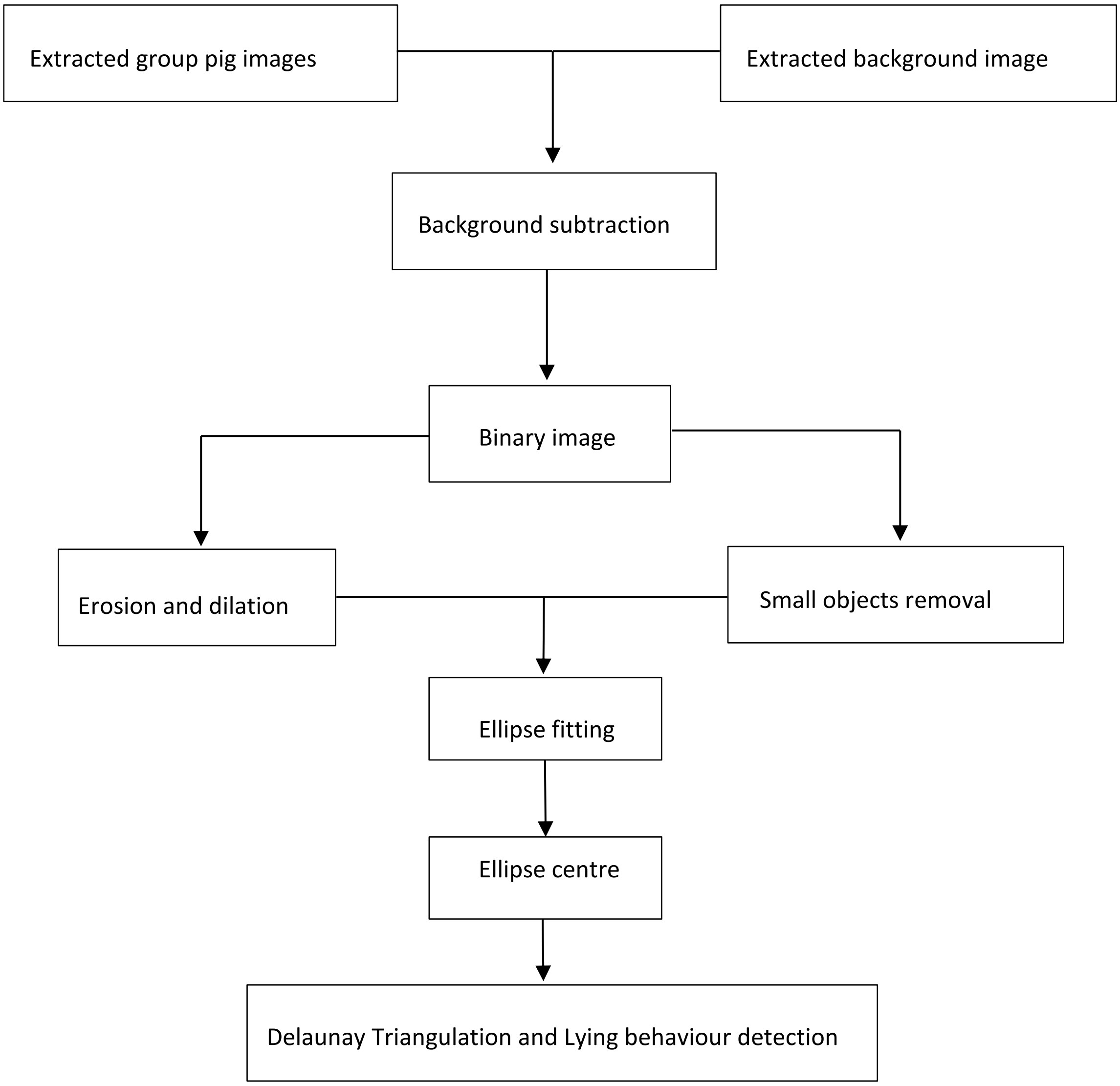


Figure 4.6- Schematic of image processing algorithm used to detect lying behaviour.

Figure 4.7 shows a sample of a DT. In this study the method used for the computation of the DT was implemented in the MATLAB® software and we used the centre of each ellipse (Figure 4.4) obtained from the image as a triangulation point. Furthermore, for obtaining a set of non-overlapping triangles with the minimum of inner angles was used, at first the algorithm in the MATLAB® transformed the 2D points to 3D, here it computed the convex hull in 3D, and then projected the lower part of the hull back to 2D to obtain the triangulation (Häfner et al., 2012).

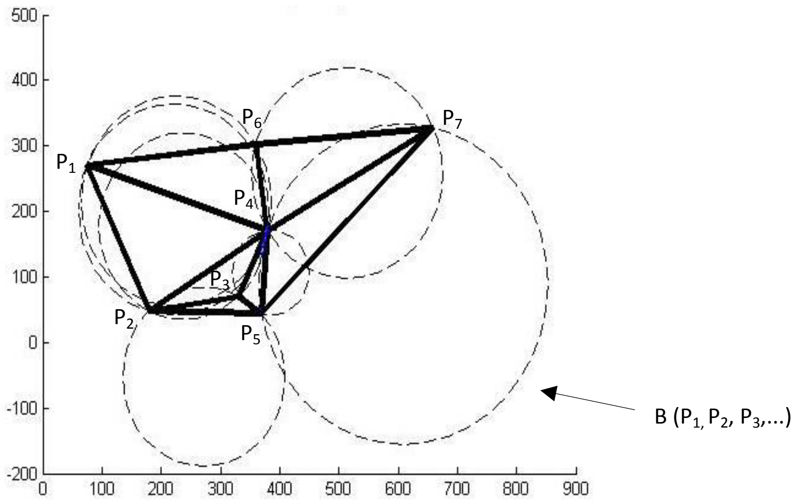


Figure 4.7- The Delaunay Triangulation (DT) for the point set P_1, P_2….P_7 in a plane. B is the circumscribing circle of Delaunay triangle.

Figure 4.8 shows the channel with 22 vertexes (number of pigs) of a sample image from the image database along with the DT.

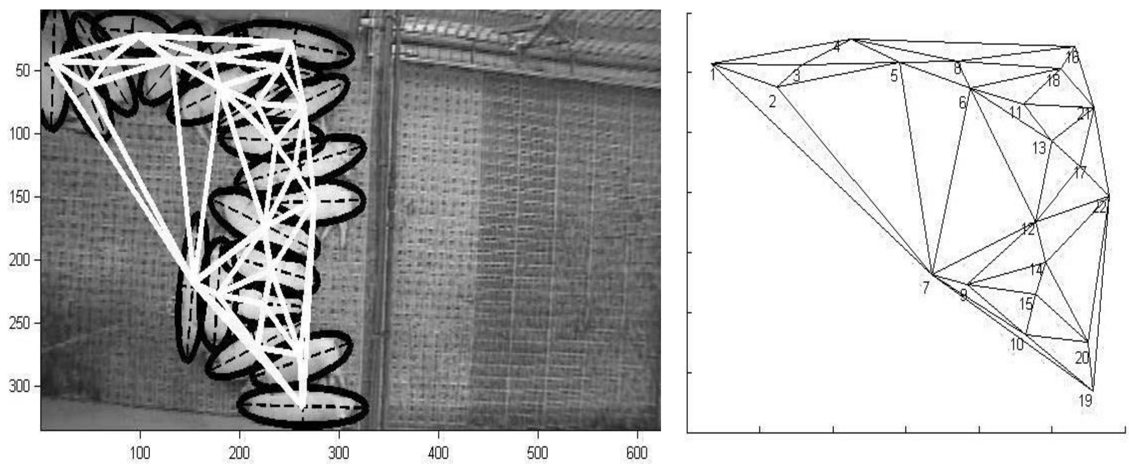


Figure 4.8- The Delaunay Triangulation (DT) along with the fitted ellipse on lying pigs.

The perimeter of each triangle in the DT shape reflects how closely pigs touch each other, and is calculated as: $P = l1 + l2 + l3$ where l represents the length of side of the triangle (in pixels). In order to find pigs' lying positions during the lying times, each pen was virtually subdivided into four zones (Figure 4.9); zone one against the outer wall and zone four being near the corridor. The centroid of each fitted ellipse indicated the specific position of each pig in the pen during the lying time.

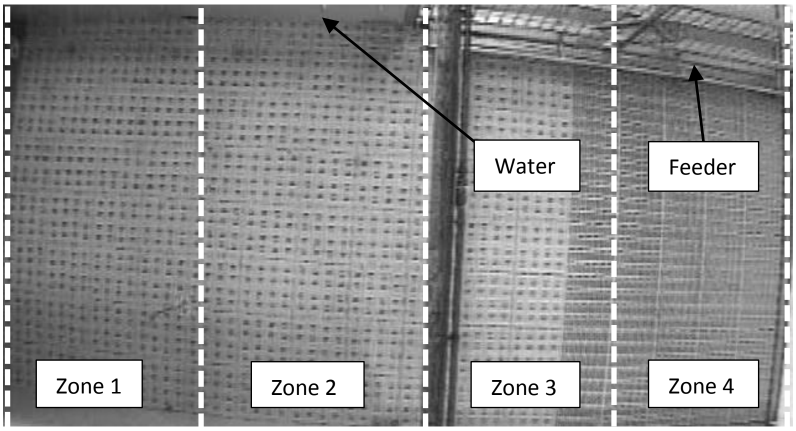


Figure 4.9- Top view of a pen indicating the four designated zones.

4.4. Lying pattern definition

To define lying patterns and model these by neural networks, four pens were selected from the 12 pens in a room (each containing 22 pigs) and a studied over a period of 15 days for the experiment (Figure 4.10). The experiment was carried out on two occasions (cold and warm seasons) giving different room temperatures. These ranged from 14 ^{o}C in the first days as the batch started in the cold season, up to 28 ^{o}C in warm situations; the room set point temperature was 21 ^{o}C during both the study periods but was not always achieved at more extreme external temperatures.

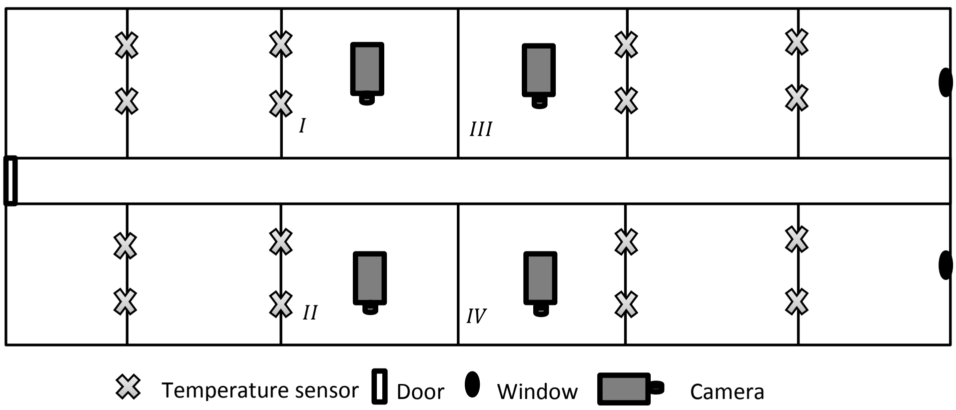


Figure 4.10- Top view of research room and the four pens used for the study on lying pattern modelling and definition.

The image processing approaches used for lying pattern and categorizing used in this study was shown in Figure 4.11.

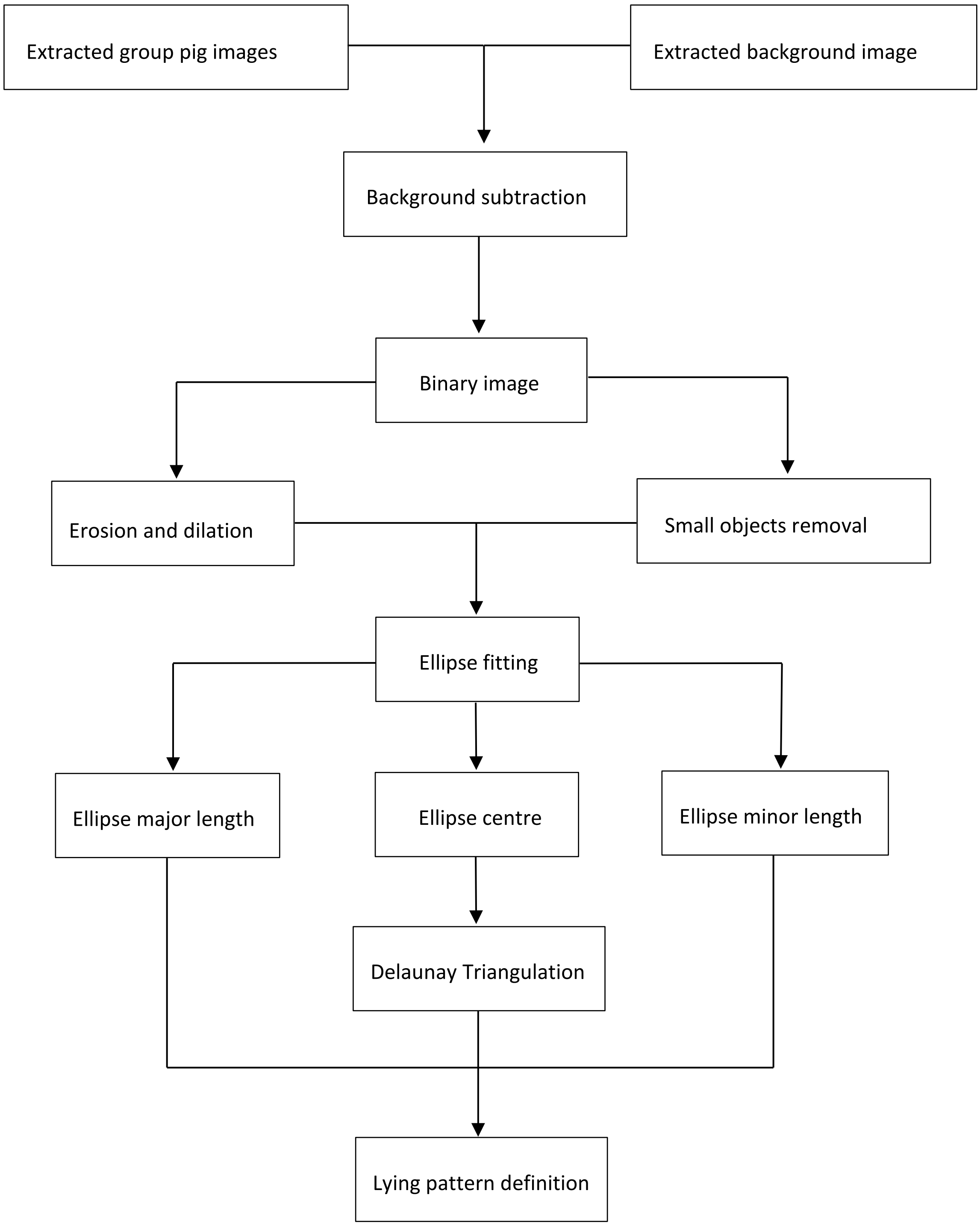


Figure 4.11- Schematic of image processing algorithm used for different lying pattern definition.

By using the major and minor axis of each fitted ellipse, the overall lying pattern was determined as the following:

$$Overall\ lying\ pattern(\%) = \left(\frac{number\ of\ triangles\ with\ certain\ pattern}{number\ of\ all\ triangles}\right) \times 100 \qquad (4.1)$$

where the certain pattern was defined as 'close pattern', 'normal pattern' or 'far pattern' based on principles which have been reported previously for pigs' lying postures in different temperatures (Table 4.1).

In cold conditions pigs crouch, sometimes shivering violently, and change their lying posture to support their body on their limbs and reduce conductive heat loss to the floor. They also huddle together to increase body contact with other pigs. In this study, we defined this as a 'close pattern'; here the size of ellipses is considered almost uniform and the number for each pig in the model can be defined in any order. Based on the principles in Table 4.1, this category was recorded if three pigs presented a pattern like those shown in Figure 4.12 (all ellipses (pigs) or at least two of the three possible pairs closely touching each other). Therefore, in a close pattern, the maximum length of side of triangle (L_{max}) and minimum length of side of triangle (L_{min}) are equal to or less than $(\frac{b_1}{2} + \frac{b_3}{2} + b_2)$ and $(\frac{b_1}{2} + \frac{b_2}{2})$, respectively (Table 4.1).

Table 4.1- Group lying patterns of pigs with their subsequent mathematical description.

Lying pattern	Lying posture	Theoretical description	Mathematical description in the study
close pattern	Sternal	Huddle together and lying close (Mount, 1968; Riskowski, 1986; Shao et al., 1998; Shao and Xin, 2008).	$L_{max} \le (\frac{b_1}{2} + \frac{b_3}{2} + b_2)$ $L_{min} \le (\frac{b_1}{2} + \frac{b_2}{2})$
normal pattern	Side-by-side	Nearly touching each other (Riskowski, 1986; Shao et al., 1998; Shao and Xin, 2008).	$(\frac{b_1}{2} + \frac{b_3}{2} + b_2) < L_{max} < (\frac{a_1}{2} + \frac{a_2}{2} + \frac{b_3}{2})$ $(\frac{b_1}{2} + \frac{b_2}{2}) < L_{min} < (\frac{b_1}{2} + b_2)$
far pattern	Spreading	Avoid touching each other, with limbs extended (Riskowski, 1986; Hahn et al., 1987; Shao et al., 1998; Hillmann et al., 2004).	$L_{max} \ge (\frac{a_1}{2} + \frac{a_2}{2} + \frac{b_3}{2})$ $L_{min} \ge (\frac{b_1}{2} + b_2)$

L_{max}= maximum length of side of triangle, L_{min}= minimum length of side of triangle
a=major axis of fitted ellipse, b= minor axis of fitted ellipse

In warm conditions, pigs try to avoid touching each other, the limbs are stretched out and pigs lie extended on their side (Table 4.1). The image processing data showed patterns like those in Figure 4.12, defined as 'far pattern'. If three pigs are touching each other from head to head or head to tail (as sometimes happened in warm conditions), the L_{max} is greater than or equal to $(\frac{a_1}{2}+\frac{a_2}{2}+\frac{a_3}{2})$; furthermore, if three pigs do not touch or two partly touch and the third is far from the others (as happens in grouped pigs), the L_{max} is greater than or equal to $(\frac{a_1}{2}+\frac{a_2}{2}+\frac{b_3}{2})$. L_{min} in far patterns is greater than or equal to $(\frac{b_1}{2}+b_2)$ (Table 4.1). In normal temperature conditions, pigs lie nearly touching each other and the resulting pattern is between the close and far patterns (Figure 4.12), defined as 'normal pattern' (Table 4.1).

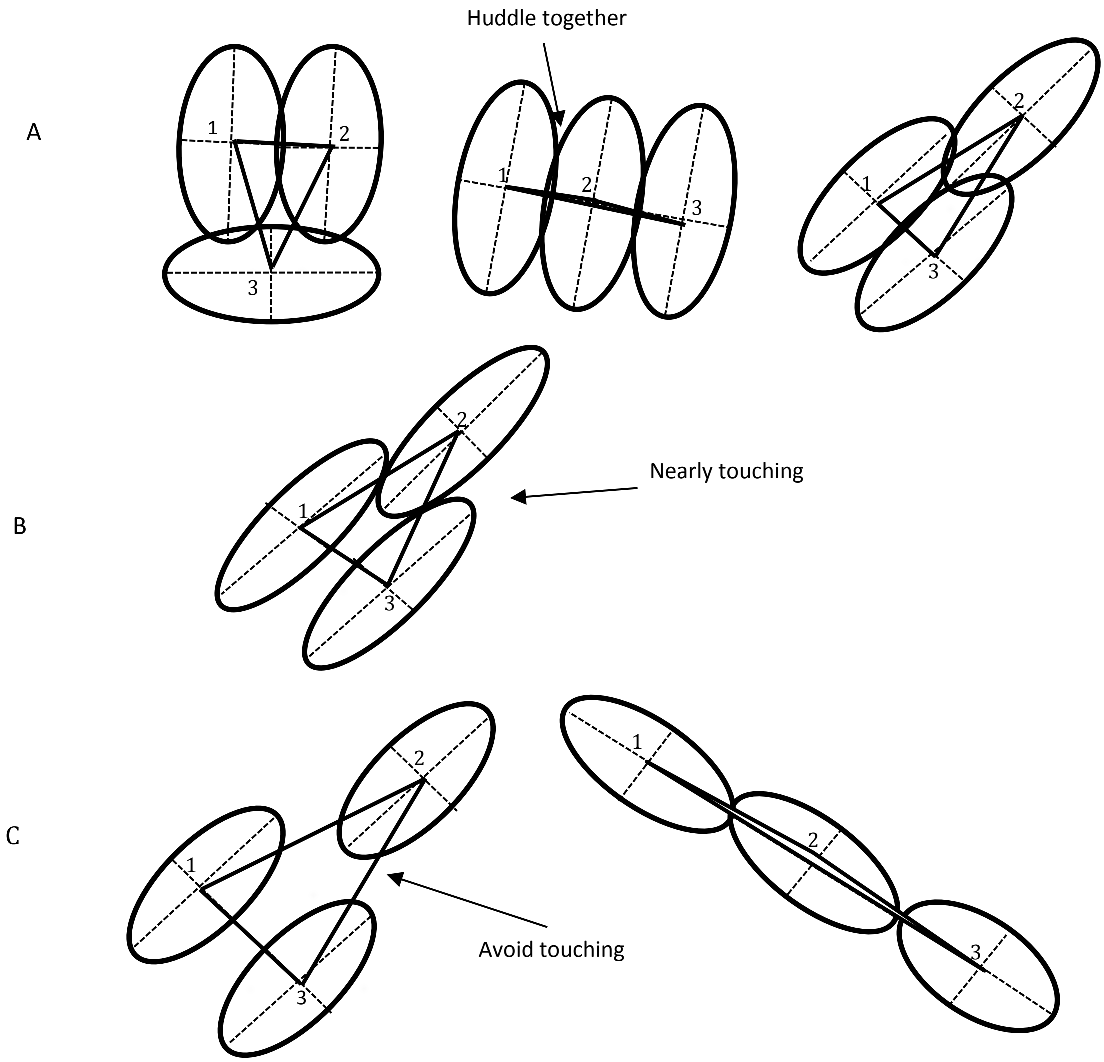


Figure 4.12- Fitted ellipses in different lying patterns; (A) Touching ellipses with their parameters and a triangle of DT in cold situations (close pattern), (B) in normal situations (normal pattern), (C) in warm situations (far pattern).

4.5. Lying pattern categorizing by artificial neural network

Figure 4.13 indicates the image processing algorithm used for categorizing pigs lying pattern in different ambient temperatures.

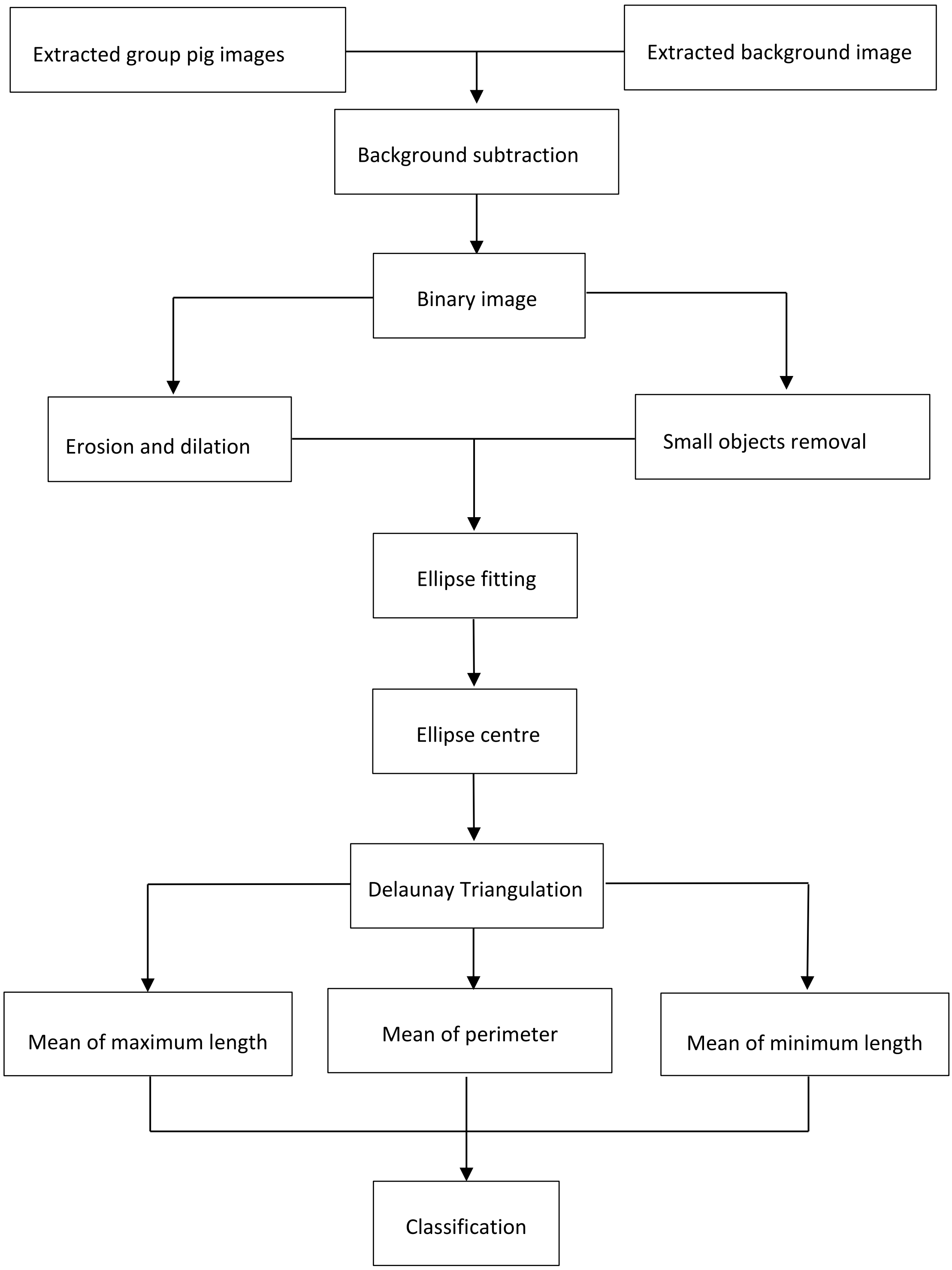


Figure 4.13- Schematic of image processing algorithm used for categorizing lying pattern by the ANN.

A MLP was employed in the MATLAB® software as the modelling network for classification. The MLP network applied here had four layers: an input layer, two hidden layers and an output layer. The number of neurons in the input layer was dependent on the number of features extracted from each triangle of the DT; in this study the perimeter (P), L_{max} and L_{min} of side of each triangle were calculated. Then the mean value of perimeter (MVP) of triangles, mean value of maximum lengths (MVL_{max}), mean value of minimum lengths (MVL_{min}) of side of triangles in each DT were considered as inputs for the ANN (3 neurons). The output layer was equal to the number of categories (Figure 4.14); in this case the room temperatures was divided into 3 thermal categories which were based on the room set point temperature: first for temperatures around (± 2 ^{o}C) the room set temperature (ARST; 19-23 ^{o}C), next for lower than the room set temperature (LRST; 14-18 ^{o}C), and third for those higher than the room set temperature (HRST; 24-28 ^{o}C). The categories LRST, ARST and HRST were represented with the sets of numbers 100, 010, 001, respectively. In order to simplify the problem with different ranges of values for the network, the dataset was normalized within the range [0, 1] to achieve fast convergence and to ensure that all variables received equal attention during the process.

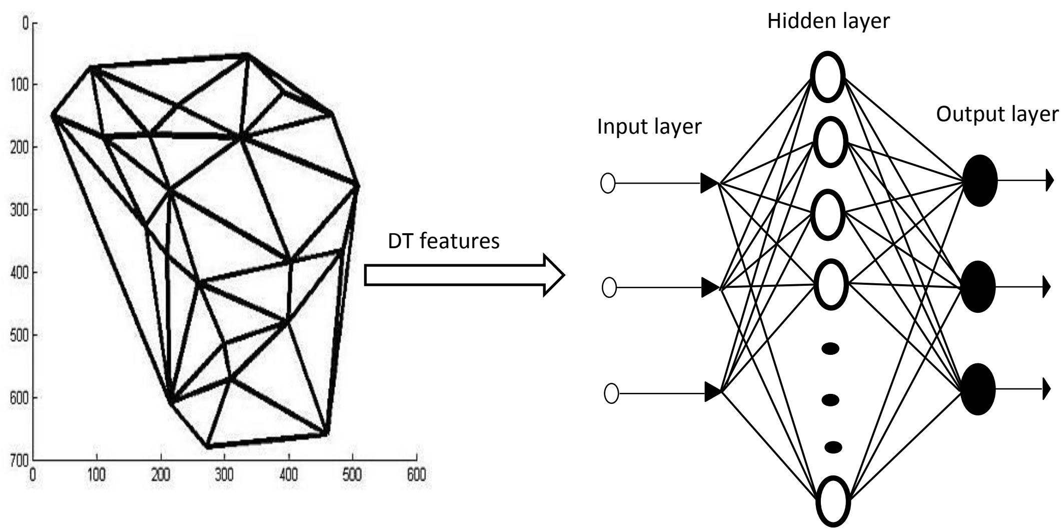


Figure 4.14- Architecture of the network along with the Delaunay Triangulation (DT) features as inputs.

The learning procedure for developing a neural network can be either supervised or unsupervised. The supervised learning algorithm used in this research was the back propagation algorithm (Chandraratne et al., 2007). Before updating the weights once at the end of the epoch, this algorithm gets the average gradient of the error surface across all cases and minimises the Mean Square Error (MSE) between input layer values and output layer values. In order to achieve the optimum hidden layer, a trial and error procedure was used by trying various numbers of neurons and layers to build the network (Mashaly and Alazba, 2016) and the network which gave the lowest MSE of the verification subset was chosen. The two hidden layers of the selected network had different numbers of neurons (16 and 22, respectively). Lastly, the selected MLP network with 3-16-22-3 was used to evaluate the ability of this multivariable technique for classification. In this study the MLP used a tansig function ($\mathrm{y} = \mathrm{tansig}\ (\mathrm{x}) = \frac{2}{1+\mathrm{e}^{-2\mathrm{x}}} - 1$) in the hidden layers and linear function ($\mathrm{y} = \mathrm{x}$) in the output layer.

Data sets of 1800 observations with 600 observations (5 temperatures in each category × 120 frames for each temperature) for each of the three thermal categories were used. The ANNs were trained on the first subset (training set), and their performance was monitored using the second subset (validation set). In this method the network stops the training before overfitting occurs, which is a technique automatically provided for all supervised networks in the MATLAB® Neural Network Toolbox™. Finally, the last subset (test set) was used to check the predictive performance of the network, since the data included in this subset were not used in the network development. Experimental data sets were randomly divided into training (70%; 1260 observations), validating (15%; 270 observations), and testing (15%; 270 observations) sets. For finding the classification performance, the sensitivity, specificity and accuracy (category-specific and the model's overall performance) were computed based on the following definitions (Grzesiak et al., 2010; Pourreza et al., 2012):

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \tag{4.2}$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{4.3}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \tag{4.4}$$

TP: Samples of a specific category correctly classified as that category. FN: Samples of a specific category incorrectly classified as other categories. TN: Samples of other categories correctly classified as their categories. FP: Samples of other categories incorrectly classified as the specific category.

Assessment of the discrimination accuracy between different classes of individual models also involved the relative operating characteristic (ROC), which was computed in MATLAB® based on true positive and false negative rates (Pearce and

Ferrier, 2000; Fawcett, 2006) and can be used for assessment of binary classifiers (Barnes et al., 2010)

$$Sensitivity + false\ negative\ rate = 1 \quad (4.5)$$

$$Specificity + false\ positive\ rate = 1 \quad (4.6)$$

Eq. (4.5 and 4.6) can be written as (Pearce and Ferrier, 2000):

$$\left(\frac{w}{x} = 1\right) + \left(\frac{v}{x} = 1\right) = 1 \quad (4.7)$$

$$\left(\frac{w}{x} = 0\right) + \left(\frac{v}{x} = 0\right) = 1 \quad (4.8)$$

where *w* is a predicted output greater or equal to the threshold probability, and *v* is a predicted output less than the threshold probability. In ROC, two values are calculated for each threshold: the true positive rate (the number of *w*, divided by the number of 1 targets), and the false positive rate (the number of *v*, divided by the number of 0 targets) (Pearce and Ferrier, 2000). The area under the ROC curve (AUC) reflects the proportion of the total area of the unit square and ranges from 0.5 for models with no discrimination ability, to 1 for models with best discrimination.

4.6. Lying behaviour monitoring after enrichment substrate provision

To assess the effect of a rooting material on the lying behaviour, six pens were selected for the experiments from the 12 pens in a room, each containing 17-20 pigs (Figure 4.15).

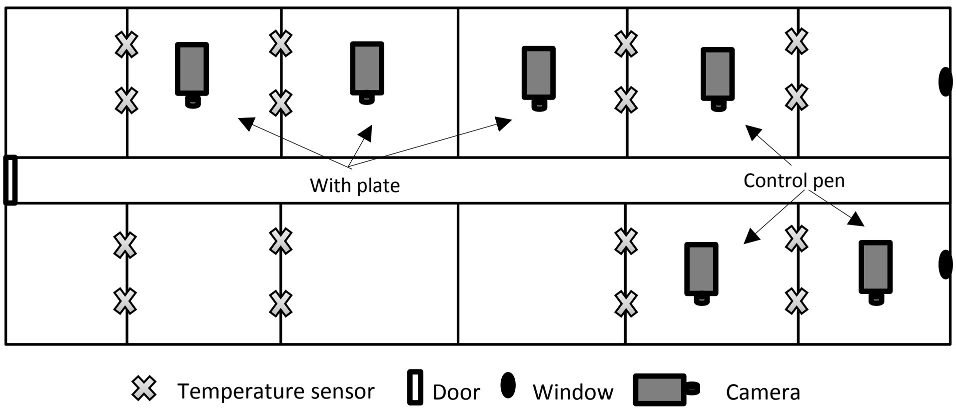


Figure 4.15- Top view of research room and six pens used for studies on lying positions with enrichment substrate.

In each of two replicates, three pens were equipped with a solid plate (1m × 1m) on the floor in the lying area to allow for delivery of rooting material, while the other three had no plate and only a hanging plastic toy for enrichment. The experimental phase started after placement of pigs in the pen at approximately 30 kg live weight, and lasted to the end of the batch. The enrichment material provided was chopped maize silage (10kg per day for each pen) and was manually distributed once in a day, at approximately 9 AM, onto the floor plate in the experimental pens. Extracted images from video files were analysed according to the scheme presented in Figure 4.16 using MATLAB® software.

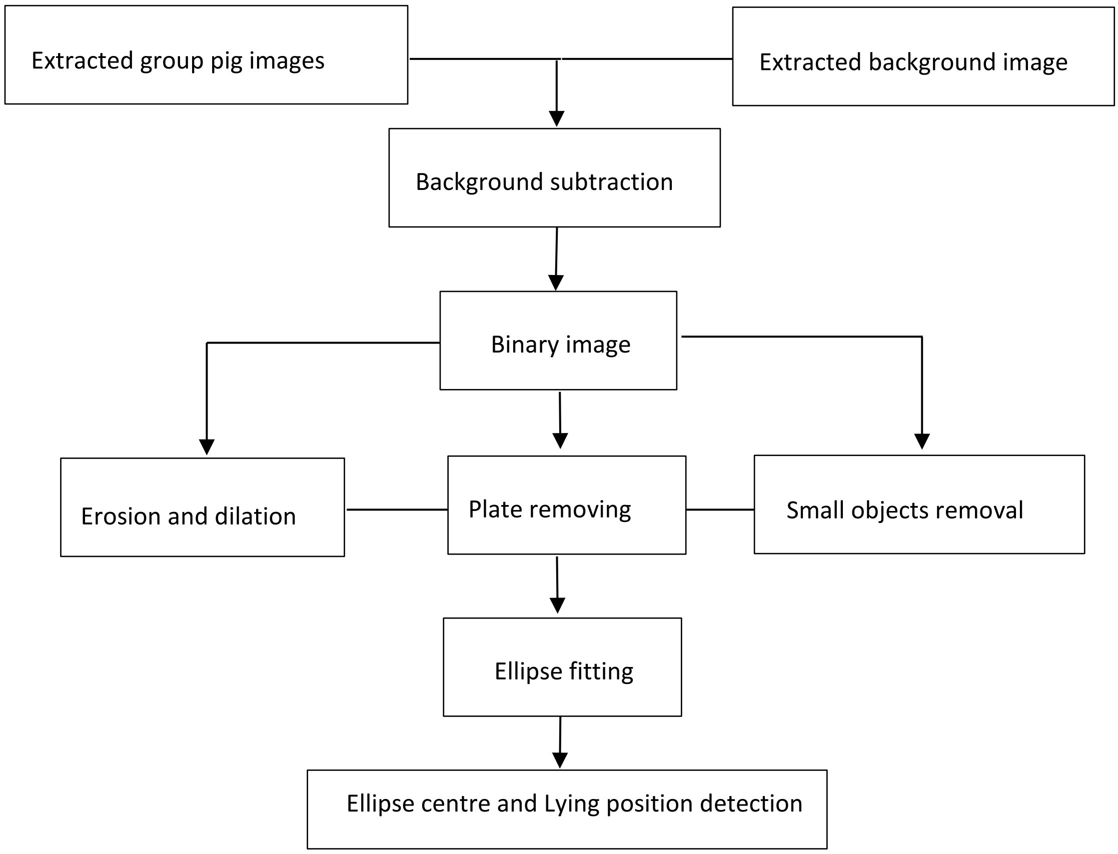


Figure 4.16- Schematic of image processing algorithm used for monitoring the effect of rooting material on grouped pig lying positions.

To develop algorithms for continuous automated identification of changes in the lying position of the pigs, the location of each group of pigs needs to be known during defined periods. Animal lying positions were obtained at 10 minute intervals for 10 separate days across the duration of the batch period (with 5 day intervals) for two replicates of the study over time. Each pen was virtually subdivided into four zones in the extracted frame from video files as previously described. Similarly, the centroid of each fitted ellipse was used in order to find pigs' lying position in the pen in x-y coordinates (Figure 4.17).

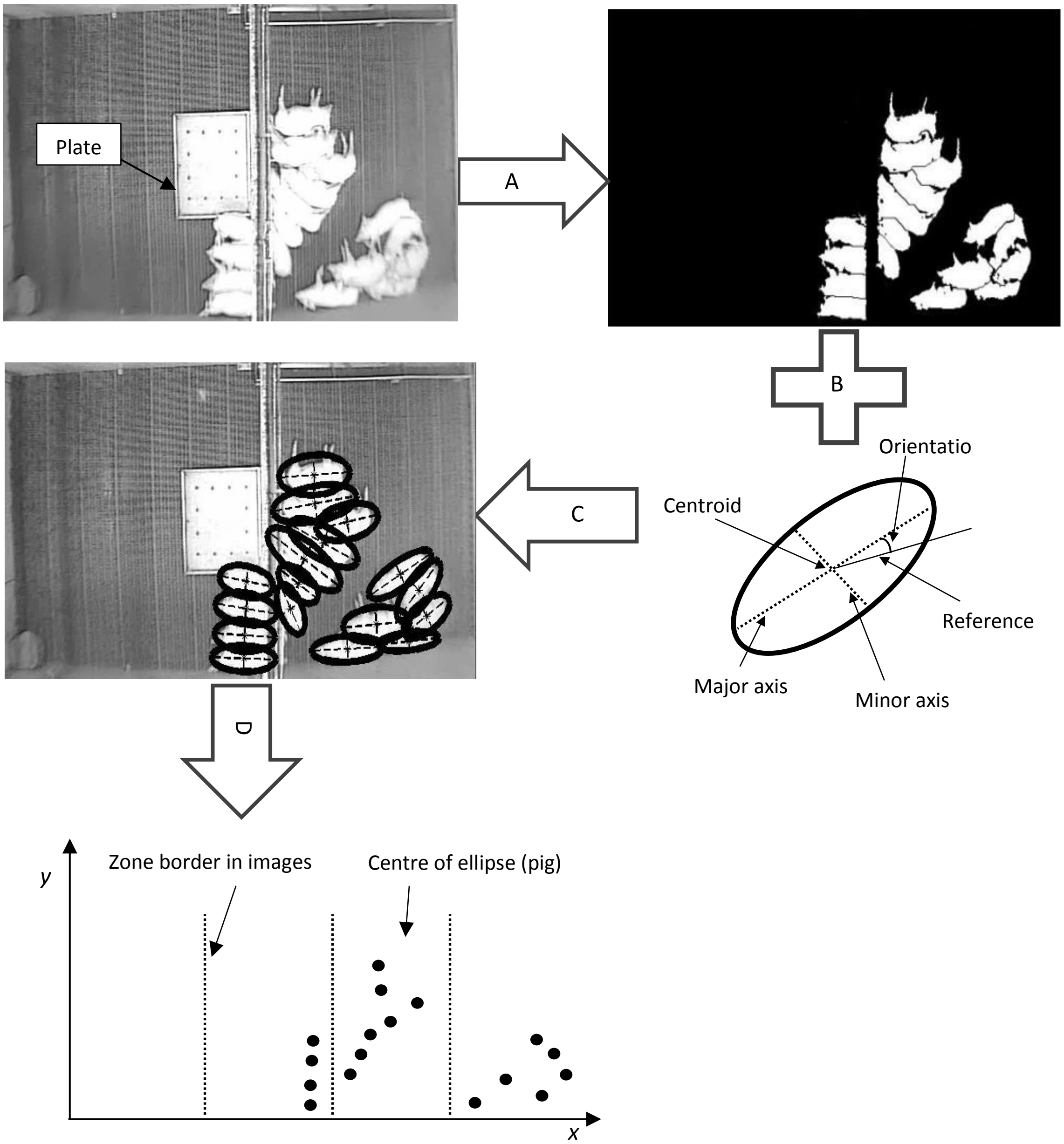


Figure 4.17- Lying position detection; converting grey image to binary and removing small objects (A), using ellipse features for fitting ellipse to each pig (B), fitting ellipse to each pig (C), finding the centre of each fitted ellipse in x-y coordinates (D).

To compare activity levels and lying locations of pigs between the two treatments, using the full dataset from the image processing output, the total proportion of the pigs which were lying, and the proportion of lying pigs in each zone of the pen were analysed using the MIXED procedure in SAS software (Statistical Analysis System; SAS®, 9.4 version for Windows). The model used for all analyses was treatment (rooting plate or control pen), stage of growth (day) and time of day (hour) as fixed effects and, following testing of separate interaction effects and removal of nonsignificant interactions, included the interaction between treatment and time of day; time of day (hour) was included as the repeated factor.

4.7. Mounting event detection

To define mounting events in this study, two pens (Figure 4.5) were selected for the experiment from the 12 pens in a room, each containing 22–23 pigs of mixed entire males and females, and studied for 20 days. After downloading the recorded data, the video files were directly observed and labelled in order to evaluate peak times of mounting activity (Hintze et al., 2013). A sufficient number of occurrences of the behaviour for testing the automated approach were obtained using five days of 24 h activity selected from the available sample. Two periods were selected (2 h between 09:30 to 11:30 AM; 3 h between 14:30 to 17:30 PM) for each day and pen, during which the number of mounting events was increased compared to other periods. The selected video files were then used for extracting frames for further processing as illustrated in Figure 4.18.

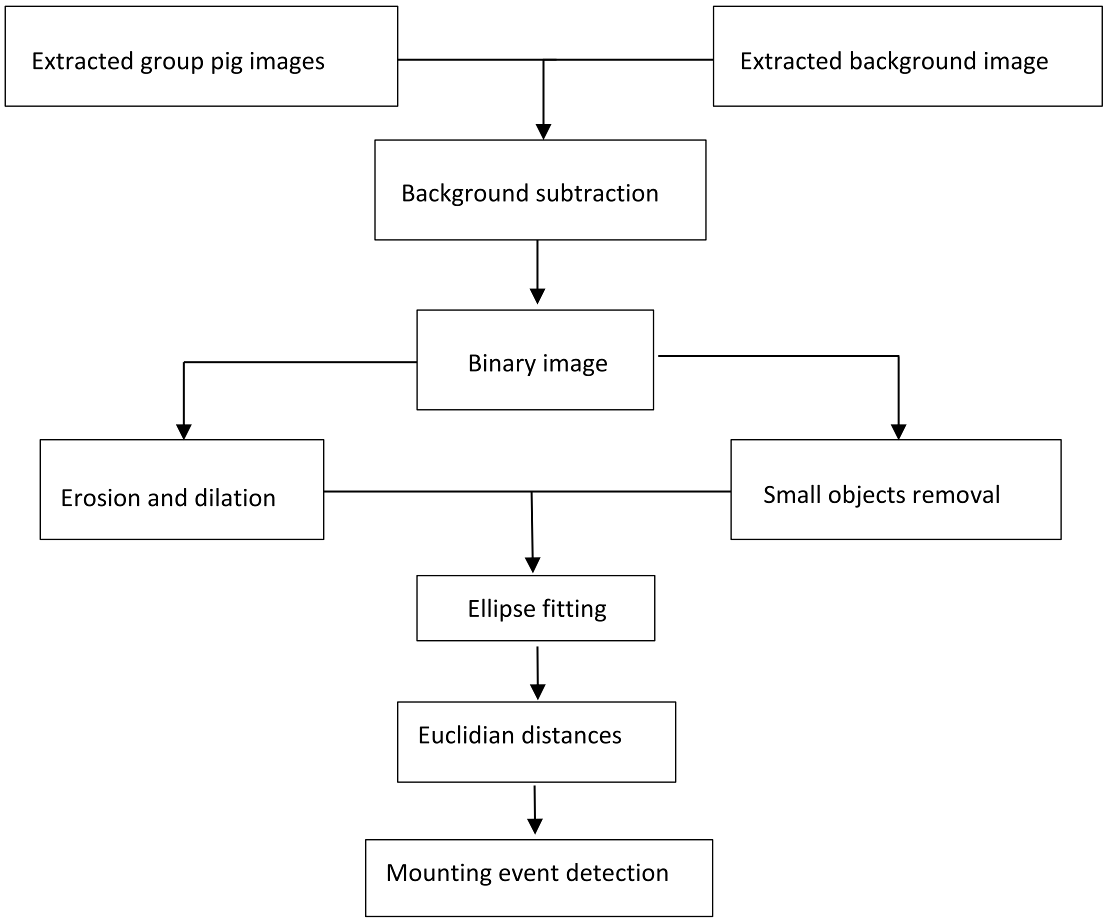


Figure 4.18- Schematic of image processing algorithm used for pig mounting event detection.

The detection rule for pig mounting events in frame sequences is based on distance between pigs, as normally a mounting pig gets close to another pig and then lifts its two front legs and puts them on any part of the recipient or mounted pig (Figure 4.19).

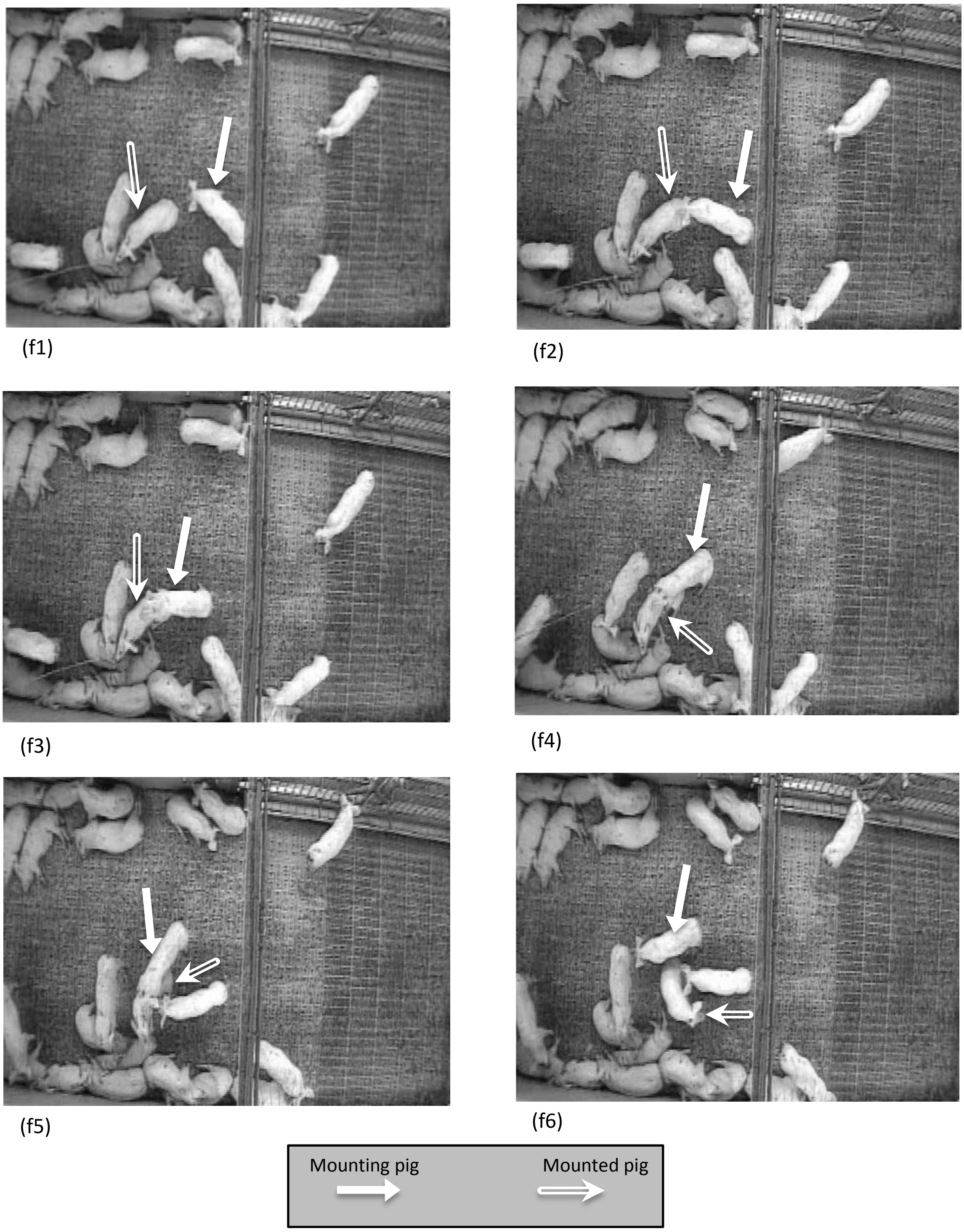


Figure 4.19- Mounting behaviour in pigs: (f1- f2) getting close, (f3-f5) mounting happened, (f6) getting away/mounting finished.

The mounted pig may stand, sit down or run away, and the duration of mounting can be short (<1s), medium (1-10s) or long (>10-60s) (Hintze et al., 2013). Figure 4.19 illustrates a video sequence for a mounting event in a pen, where in frames (f1-f2) the distance between two pigs (mounting and mounted) became less; this distance could be between the centre of two pigs or the head of one pig to the tail of the next one. The mounting event happened in frames (f3-f5), in frame (f6) the mounting/mounted pig moved away and the event finished.

In order to find the distance between two pigs in a mounting event, it was necessary to identify the head, tail and two sides of pigs. As a tool, analysis of the body contour of a pig was suggested by Kashiha et al. (2013), but in this study the long distance from the lens (camera) to the object (pig), low quality of images and the background noise made the method inaccurate. Therefore, in this work, the intersections of the major and minor axis with the ellipse have been considered as tail/head and sides respectively (Figure 4.20), named as T, H, S and then the Ed ($Ed\ (H_i, T_j)) = \sqrt{\sum_{i=1}^{n}(H_i - T_i)^2}$ and $(Ed\ (H_i, S_j)) = \sqrt{\sum_{i=1}^{n}(H_i - S_i)^2}$ of each pair was calculated as follows:

$$\text{Matrix of head and/or tail for n pigs (T, H):} \begin{bmatrix} T_1 & H_1 \\ T_2 & H_2 \\ . & . \\ . & . \\ . & . \\ . & . \\ . & . \\ . & . \\ T_{n-1} & H_{n-1} \\ T_n & H_n \end{bmatrix} \tag{4.9}$$

$$\text{Matrix of pig sides for n pigs (S, S):} \begin{bmatrix} S_1 & S_2 \\ S_3 & S_4 \\ . & . \\ . & . \\ . & . \\ . & . \\ . & . \\ . & . \\ S_{2n-3} & S_{2n-2} \\ S_{2n-1} & S_{2n} \end{bmatrix} \tag{4.10}$$

$$\xrightarrow{(Eq.4.9)} Ed(T_1, \begin{bmatrix} H_2 \\ H_3 \\ . \\ . \\ H_{n-1} \\ H_n \end{bmatrix}), Ed(T_2, \begin{bmatrix} H_1 \\ H_3 \\ . \\ . \\ H_{n-1} \\ H_n \end{bmatrix}) \;....\; Ed(T_n, \begin{bmatrix} H_1 \\ H_2 \\ . \\ . \\ H_{n-2} \\ H_{n-1} \end{bmatrix}) \tag{4.11}$$

$$\xrightarrow{(Eq.4.9)} Ed(T_1, \begin{bmatrix} T_2 \\ T_3 \\ . \\ . \\ T_{n-1} \\ T_n \end{bmatrix}), Ed(T_2, \begin{bmatrix} T_1 \\ T_3 \\ . \\ . \\ T_{n-1} \\ T_n \end{bmatrix}) \;....\; Ed(T_n, \begin{bmatrix} T_1 \\ T_2 \\ . \\ . \\ T_{n-2} \\ T_{n-1} \end{bmatrix}) \tag{4.12}$$

$$\xrightarrow{(Eq.4.9)} Ed(H_1, \begin{bmatrix} H_2 \\ H_3 \\ . \\ . \\ H_{n-1} \\ H_n \end{bmatrix}), Ed(H_2, \begin{bmatrix} H_1 \\ H_3 \\ . \\ . \\ H_{n-1} \\ H_n \end{bmatrix}) \;....\; Ed(H_n, \begin{bmatrix} H_1 \\ H_2 \\ . \\ . \\ H_{n-2} \\ H_{n-1} \end{bmatrix}) \tag{4.13}$$

$$\xrightarrow{(Eq.\ 4.9\ and\ 4.10)} Ed(T_1, \begin{bmatrix} S_3 \\ S_4 \\ . \\ . \\ S_{2n-1} \\ S_{2n} \end{bmatrix}), Ed(T_2, \begin{bmatrix} S_1 \\ S_2 \\ . \\ . \\ S_{2n-1} \\ S_{2n} \end{bmatrix}) \;....\; Ed(T_n, \begin{bmatrix} S_1 \\ S_2 \\ . \\ . \\ S_{2n-3} \\ S_{2n-2} \end{bmatrix}) \tag{4.14}$$

$$\xrightarrow{(Eq.\ 4.9\ and\ 4.10)} Ed(H_1, \begin{bmatrix} S_3 \\ S_4 \\ . \\ . \\ S_{2n-1} \\ S_{2n} \end{bmatrix}), Ed(H_2, \begin{bmatrix} S_1 \\ S_2 \\ . \\ . \\ S_{2n-1} \\ S_{2n} \end{bmatrix}) \;....\; Ed(H_n, \begin{bmatrix} S_1 \\ S_2 \\ . \\ . \\ S_{2n-3} \\ S_{2n-2} \end{bmatrix}) \tag{4.15}$$

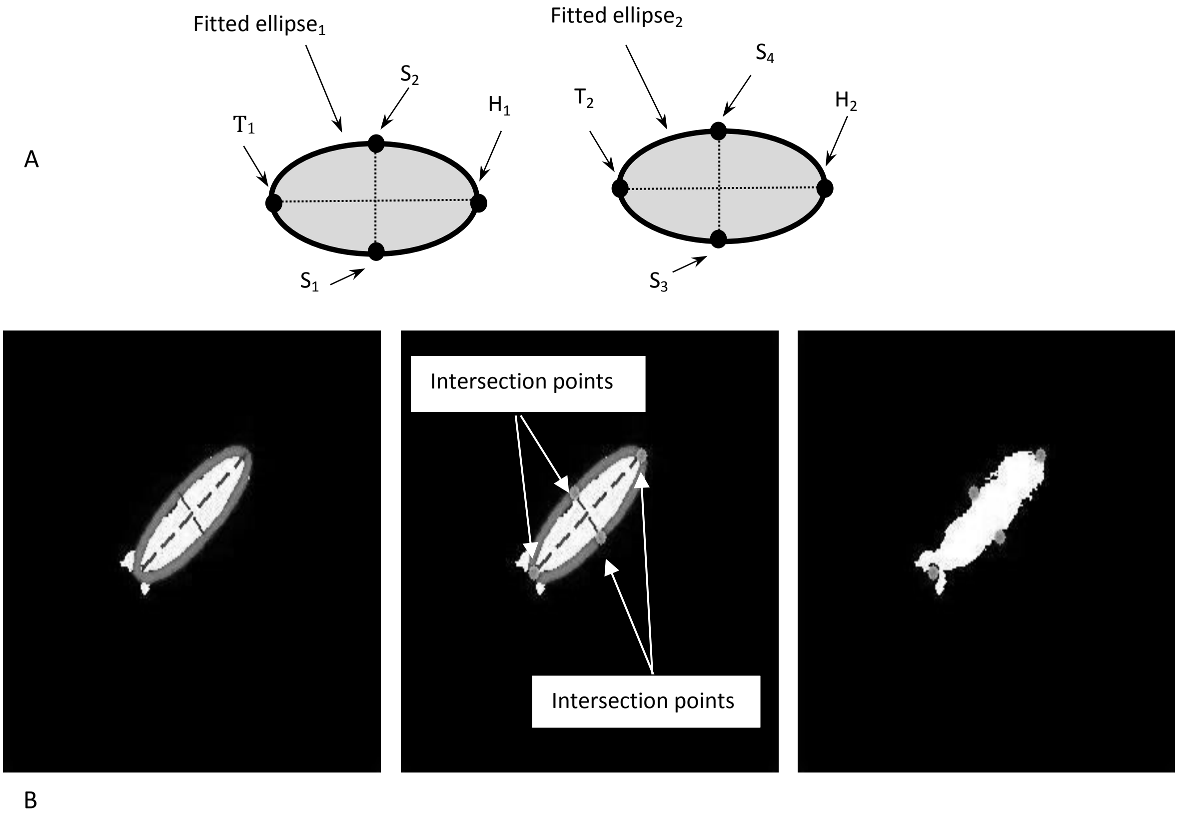


Figure 4.20- Intersection points of major and minor axis and ellipse for finding the position of head, tail and sides in pigs. (A); tail (T), head (H) and side (S) in two fitted ellipses, (B); the T, H and S in a pig in binary image.

Based on the typical behaviour of pigs, they normally move forward and mount with their front legs onto a part of the mounted pig's body. As a result, in a sequence of frames, the distance from the head of one pig to the other pig (head or tail) could be obtained from its direction of movement, as well as the distances between head of one pig to both sides of other pigs. By finding the region of interest (ROI) for each participant pair (two pigs) with an Ed less than a defined value (here, about half of the major axis length), the possibility of mounting events has been investigated in the algorithm, and the *x-y* coordinates of the centre of the two pigs in the ROI recorded for the next steps. Note that as the mounting event is performed, the Ed between the head of the first pig and the tail/head or side of the second one has been reduced from the previous frame and the two pigs considered as one in the algorithm; here the length of two pigs (length of major axis in fitted ellipse) will be changed to approximately 1.3 to 2 pig lengths if the pig is mounting from behind the second one.

The length of major and minor axis will be around 1.3-1.8 pig lengths if the pig is mounting from the side of another pig. So, if the length of the ellipse(s) was between the aforementioned value and the *x-y* coordinates of the ellipse located in the ROI, the mounting behaviour was declared.

Furthermore, if two pigs were standing close to each other without any mounting event, the algorithm just fitted an ellipse to each of the pigs and no mounting behaviour was specified.

5. Results and discussion

5.1. Lying behaviour and position changes

Two pens (I and II) were selected for group pig lying behaviour and position changes in this study. In order to validate the automated image processing technique, the percentage of frames with correct estimation of the number of pigs in the pen with reference to manual labelling was determined. There were 15 (days) × 30 (min) × 4 (times in a day) × 2 (pens) of video duration, and each video consisted of 1800 frames (one frame per second). From the 108000 (15 × 30 × 60 × 4) extracted frames for each pen, 19592 were processed in pen I and 20306 frames in pen II as described in the following paragraph.

The four time periods were selected during times when almost all pigs were lying. In the case that pig(s) were not lying during the aforementioned period, the image locomotion method which was defined by Kashiha et al. (2014) was used in order to automatically select the lying pigs in each frame; after using the ellipse fitting technique, angular and linear movements of each ellipse between two consecutive frames were calculated. By visual investigation of the pigs' movement time in the video files, the first frame f_t (at time zero) and the next one f_{t+5} (after five seconds) (Figure 5.1) were selected. According to the figure, due to pig movement the angular and linear movement of the mentioned ellipse from frame f_t to f_{t+5} was changed; the pig initially had angular movement then moved from C (i_1, j_1) to C (i_2, j_2) in the next frame. Finally, after finding the pigs in motion, by removing these active pixels in the ellipse fitting algorithm we fitted ellipses to lying pigs only in the last frame (f_l).

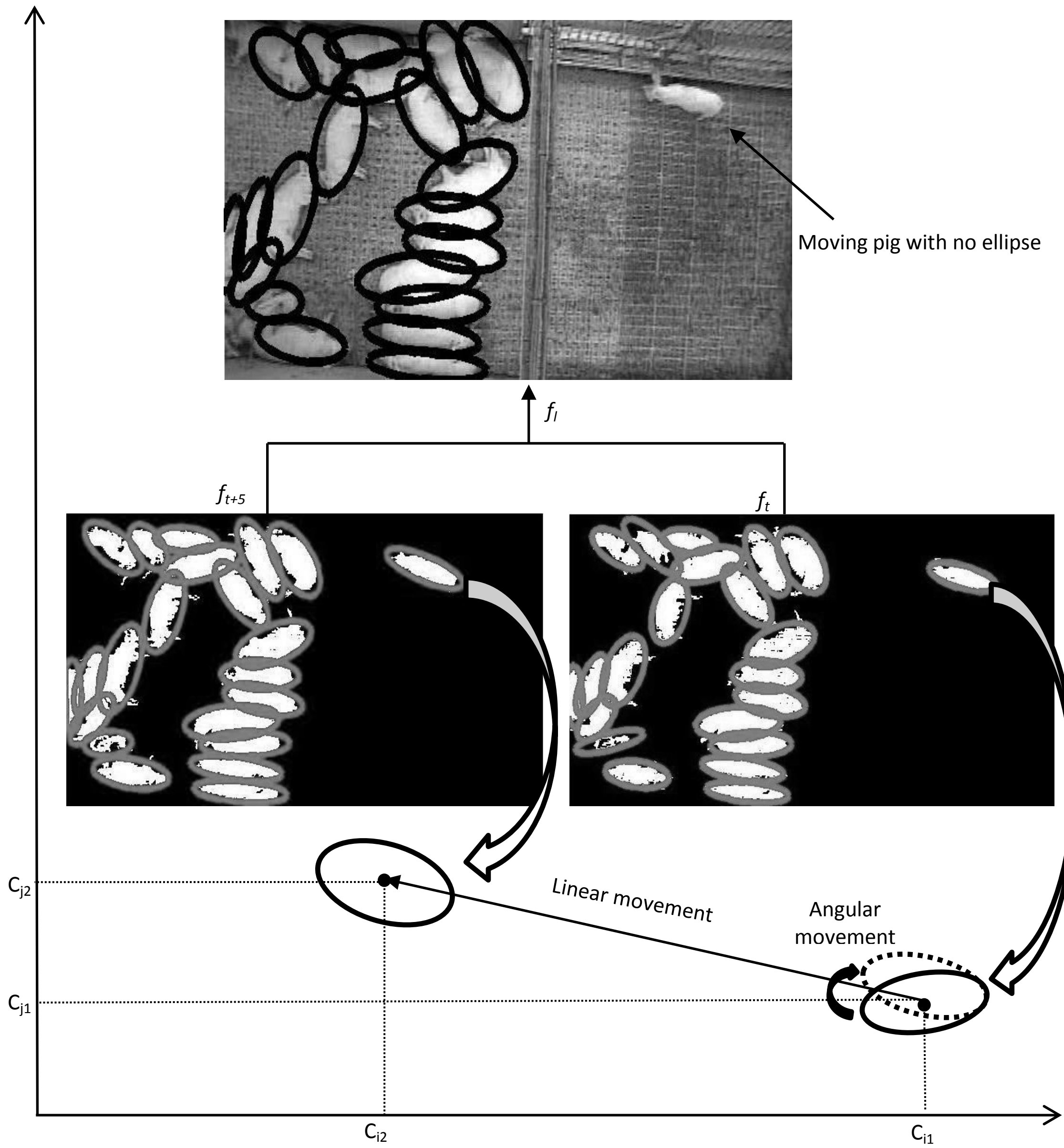


Figure 5.1- Pigs with fitted ellipse in two frames f_t and f_{t+5}, the moving pig was not selected in frame f_l and the ellipse was fitted for lying pigs in final grey image.

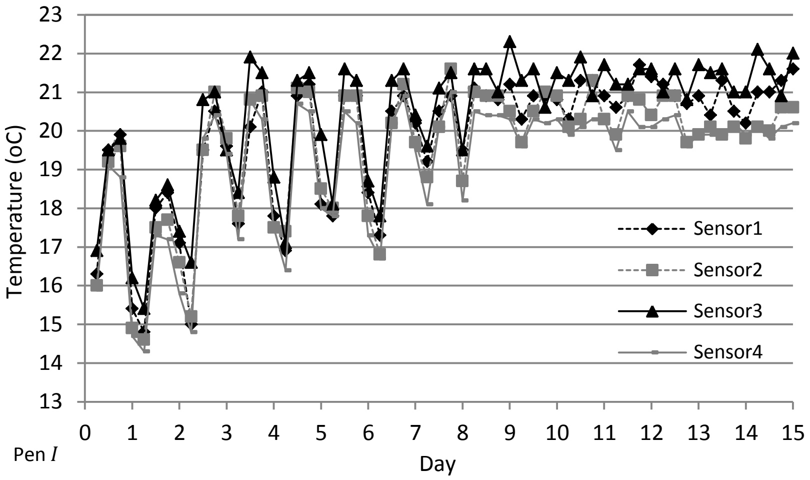
The estimated number of pigs in each processed image was calculated and then compared with the number of pigs in that pen (Table 5.1).

Table 5.1- The percentage of frames with correct estimation of pigs in the pen from automated image processing compared to manual labelling.

Day	Pen			
	I		*II*	
	Number of frames analysed	Correct estimation (%)	Number of frames analysed	Correct estimation (%)
1	1290	96.5	1359	95.0
2	1199	94.4	1378	97.6
3	1338	95.2	1400	94.9
4	1287	97.1	1321	98.3
5	1354	95.0	1298	92.6
6	1360	98.6	1387	97.7
7	1257	97.1	1385	93.2
8	1290	94.4	1355	94.0
9	1327	91.4	1375	93.9
10	1200	96.8	1342	95.3
11	1321	99.5	1370	97.3
12	1385	95.0	1346	97.0
13	1308	93.3	1321	98.5
14	1366	93.3	1295	94.2
15	1310	98.9	1374	96.3
Total	19592		20306	

The results showed that the percentage of frames with correct estimation of pigs in the pen using image processing techniques was 95.8(±2) %, on average (Table 7.1). There were a few reasons behind false identification: first and foremost because the project was carried out in a commercial farm where housing conditions could not be controlled, there was a water pipe in the middle of each pen (2.5 m from the floor) which caused some invisible areas in images. Furthermore, as time progressed, soiling by flies dirtied the camera lenses and reduced the visibility.

The averages temperatures of four sensors within each of the two pens (see Figure 4.5) during the 15 days of study are shown in Figure 5.2. Over the recording period, temperature ranges were 14.3-22.3 ^{o}C for pen I, and 13.7-22.2 ^{o}C for pen II. The temperature patterns showed more fluctuation in the first week of study and had a constant pattern in the second week, possibly because of better heat balance between the pigs' body heat emission and environmental temperature.



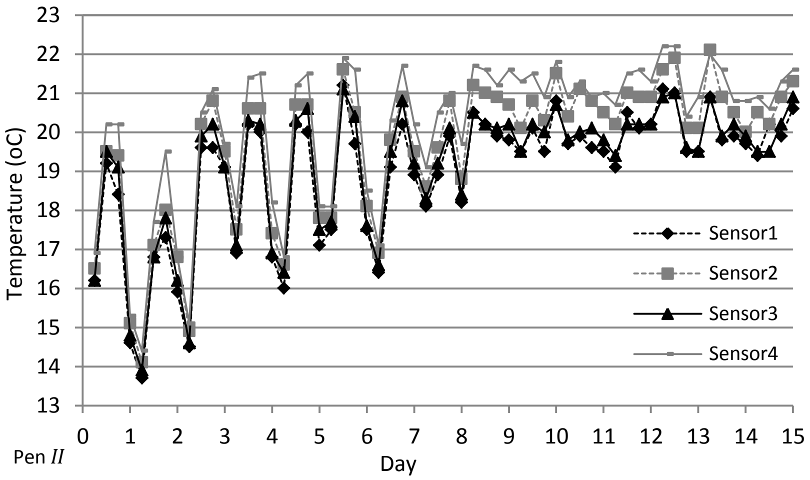


Figure 5.2- Temperature in each of the experimental pens during the 15 day study period.

Figure 5.3 shows sample images from the image database with the respective DT at different temperatures. From this figure it can be seen that the MVP of each triangle was different as average temperature changed during the study. The MVP was higher at 22.3 ^{o}C than at other temperatures, indicating that pigs had more separation during lying time at that temperature, while at lower temperature the MVP declined and pigs were lying closer or huddled together. Therefore this feature can be used for distinguishing different lying patterns in the DT and indicates that the output could be used for assessing the uniformity of room temperature for improving pig welfare.

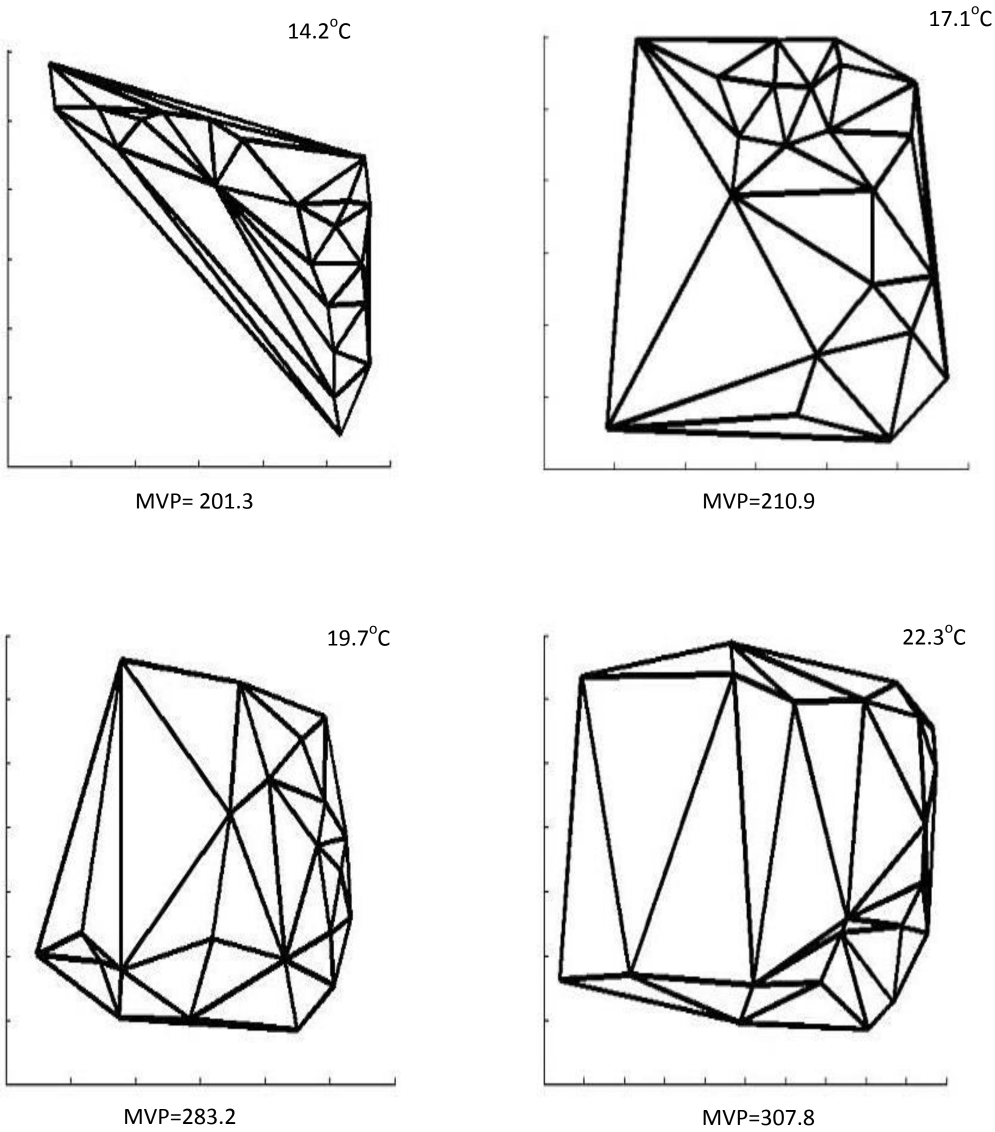


Figure 5.3- The Delaunay Triangulation (DT) patterns in different environmental temperatures.

The extracted data from the images were submitted to regression analysis (SPSS® 21, IBM, USA) to evaluate the effects of environmental temperature on the MVP in both pens (Table 5.2). The relationship between temperatures and the MVP pattern was statistically significant ($P<0.001$) for both pens.

Table 5.2- Linear regression analysis for effect of environmental temperature on the MVP in both pens.

Pen	Equation (± Std. Error)	R^2	p-value
Pen *I*	MVP= -340.3 (±29.0) + 31.3 (±2.0) temperature	0.81	<0.001
Pen *II*	MVP= -342.4 (±27.4) + 31.2 (±1.9) temperature	0.82	<0.001

MVP=mean value of perimeter

In the presented study, video monitoring of pig lying behaviour, which was performed through image processing techniques and using the DT, showed that at higher temperatures, pigs lay down with their limbs extended and in a fully recumbent position so that the MVP was higher than at lower temperatures. In contrast, at lower environmental temperatures pigs adopted a body posture that minimized their contact with the floor and maximized the contact with other pigs, so that the MVP was lower. This result is in agreement with other researchers (Shao and Xin, 2008; Costa et al., 2014) who have reported that in higher temperatures pigs tended to spread out, and in cold situations they tried to huddle or touch each other. Different MVPs in different temperatures for the two pens during this study are shown in Figures 5.4 and 5.5.

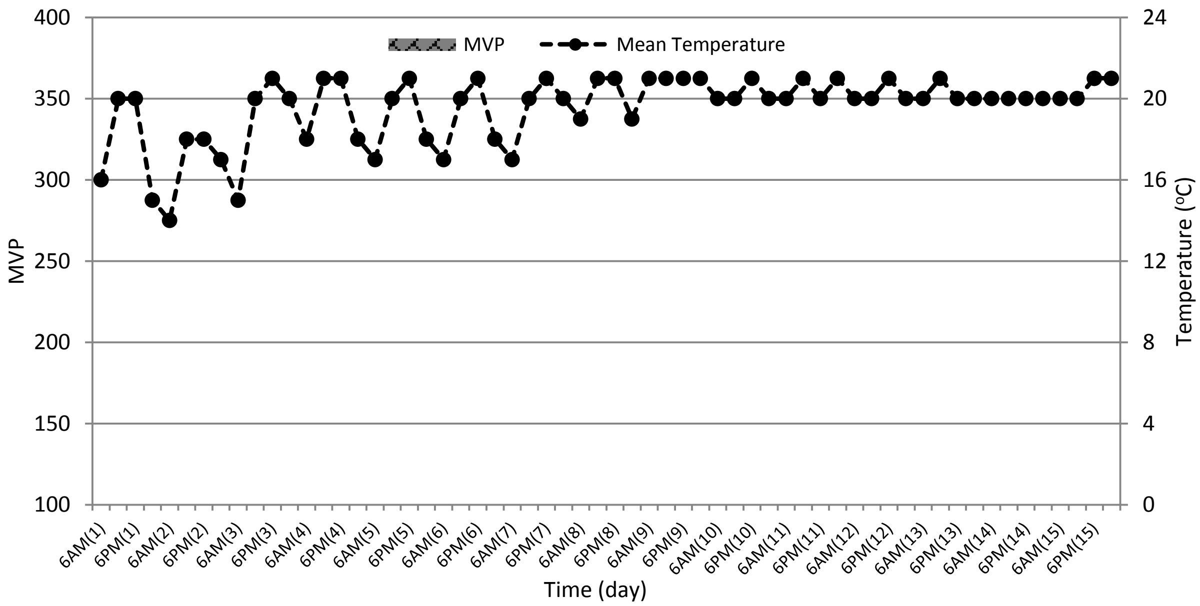


Figure 5.4- The mean value of perimeter (MVP) over 15 days assigned with their temperature (°C) in pen I.

By comparing temperatures in the two pens and according to the MVP data, pigs tended to lie further apart and had less contact in pen I (Figure 5.4) than in pen II

(Figure 5.5). In some cases the MVP was different at identical temperatures in both pens. This is likely due to additional environmental influences (i.e. different ventilation rates in different locations in each pen) which could not be controlled as the project was carried out in a commercial pig farm.

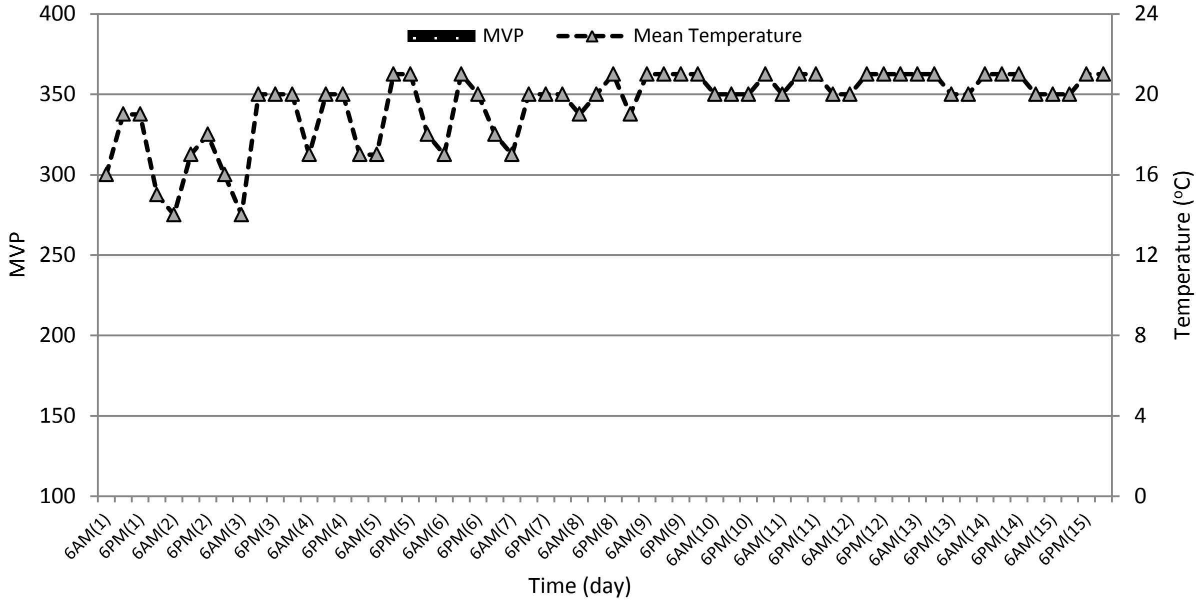


Figure 5.5- The mean value of perimeter (MVP) over 15 days assigned with their temperature (^{o}C) in pen II.

Employing modern technology has helped farm managers to improve animal welfare (Kashiha et al., 2014). The proposed method can help to monitor a large number of pigs in different commercial pens and to adjust room temperature for higher welfare and economic outputs.

Knowing the position of each pig in the pen during lying time can be used to assess and improve animal welfare, since lying in the dunging area has negative consequences for hygiene, resulting in dirtier pigs and pens (Spoolder et al., 2012). Using the *x-y* coordinates of each pig in binary images and the centroid of each fitted ellipse indicated the specific position of each pig in the pen during the lying time (see Figure 6.4). Over the 15 days, the percentage of lying positions was higher in zone 4 (near the corridor) and zone 3 when the temperature was lower in both pens; similar results were reported by Costa et al. (2014). According to Figure 5.6, in both pens pigs tended to lie in zone 4 and 3 more than other zones, but when temperature increased they tended to lie more often in zone 1 and 2. The percentage of time in different lying zones was different between the two pens during the study; in pen II more than 70% of the animals were in zone 4 for the first 6 days while there was a more even distribution between zones 3 and 4 in pen I. The lying zone which pigs choose is determined by a number of factors including design of the pen, location of feeder and drinker, and environmental conditions relating to temperature, air velocity and humidity (Spoolder et al., 2012; Costa et al., 2014). In the two investigated pens, feeder and drinker locations were the same and the temperature sensors showed almost equal values for both pens during the study. However, with the ventilation system in use, the air velocity pattern or the volume of air displacement may have differed between the pens to cause the different distribution in lying positions.

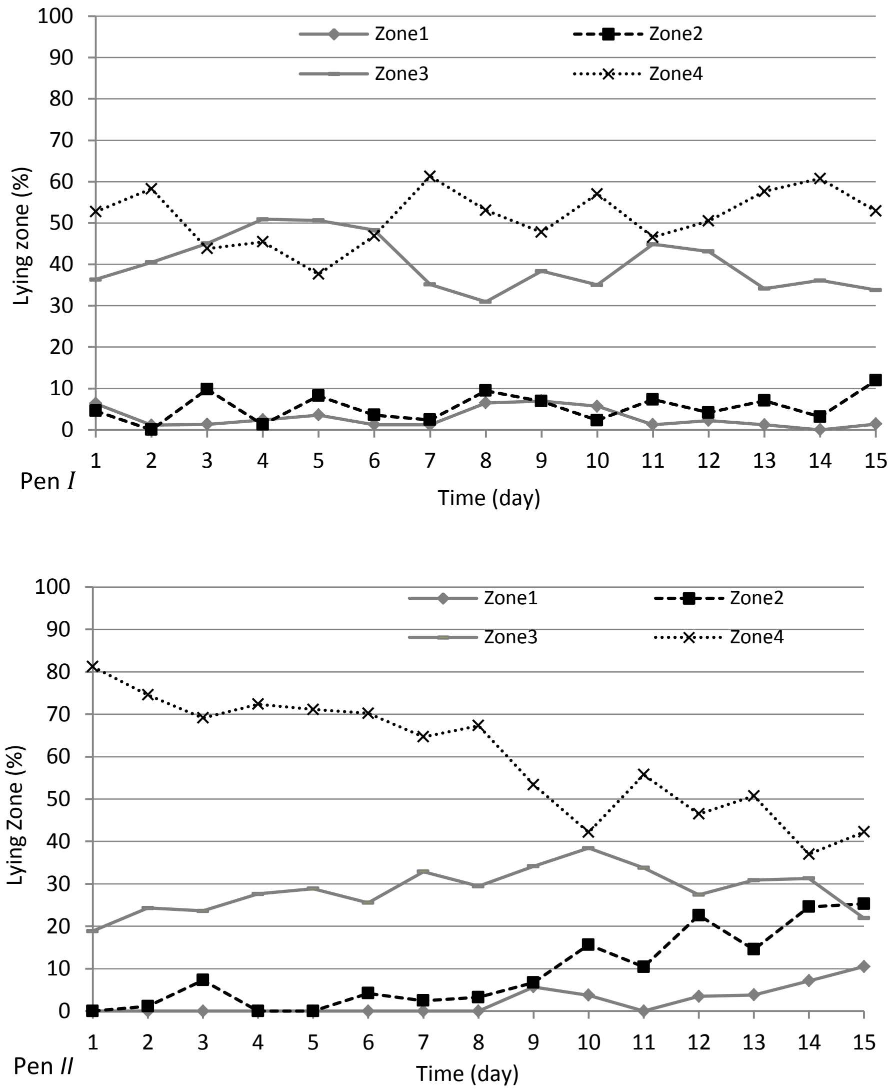


Figure 5.6- The percentage of lying pigs located in different zones over 15 days.

5.2. Lying pattern definition

Table 4.1 shows the mathematical description of L_{max} and L_{min} obtained from the lying patterns. Since the perimeter of each triangle is the sum of the length of sides (L) of each triangle, the P value (pixels) for each lying pattern is found as follows.

In the close pattern:

$$P = L_{max} + L_{min} + L \tag{5.1}$$

$$\xrightarrow{(\,Table\ 6.1\ \ and\ Eq.\ (5.1))} P \le \left(\frac{b_1}{2} + \frac{b_3}{2} + b_2\right) + \left(\frac{b_1}{2} + \frac{b_2}{2}\right) + L \tag{5.2}$$

The maximum value of P was obtained when a triangle had two L_{max} (isosceles) means:

$$L = L_{max} \tag{5.3}$$

$$\xRightarrow{Eq.\ (5.2\ and\ 5.3)} \quad P \le \left(\frac{3b_1+5b_2+2b_3}{2}\right) \tag{5.4}$$

In this study, by computing Eq. (5.4), the perimeter of each triangle to be considered as the close pattern gave P≤200 (pixels).

In the far pattern:

$$\xrightarrow{(Table\ 6.11\ and\ Eq.\ (9))} \quad P \ge \left(\frac{a_1}{2} + \frac{a_2}{2} + \frac{b_3}{2}\right) + \left(\frac{b_1}{2} + b_2\right) + L \tag{5.5}$$

When triangle had two sides with L_{min} value, so;

$$L = L_{min} \tag{5.6}$$

$$\xRightarrow{Eq.\ (5.5\ and\ 5.6)} \quad P \ge \frac{a_1+a_2+2b_1+4b_2+b_3}{2} \tag{5.7}$$

The perimeter of each triangle in the far pattern, by calculation of Eq. (5.7), gave P≥350 (pixels), with the normal pattern having perimeter values between these two, i.e. 200<P<350 (pixels).

The percentage of DT indicating pigs in each of the three lying patterns for the defined thermal categories in this study, are shown in Figure 5.7. for each mean temperature. According to this figure, in the LRST category the percentage of close pattern declined from 71.4 % to 54.8 % as the temperature increased from 14 to 18 ^{o}C; the values for both normal and far pattern were increased from 17.2 to 30.1 % and 11.4 to 15.1 %, respectively. In the ARST category, with a temperature range of 19 to 23 ^{o}C, the percentage of close pattern showed a downward trend from 46.1 to 20.2 %, while the far pattern showed an increase from 19.6 to 45.5 %. As the temperature increased in the HRST category from 24 to 28 ^{o}C, the percentage of normal and close pattern declined from 34.4 to 27% and 18.8 to 8.4%, respectively. In this category, an increase of 4 ^{o}C of temperature raised the far pattern by 16% (Figure 5.7).

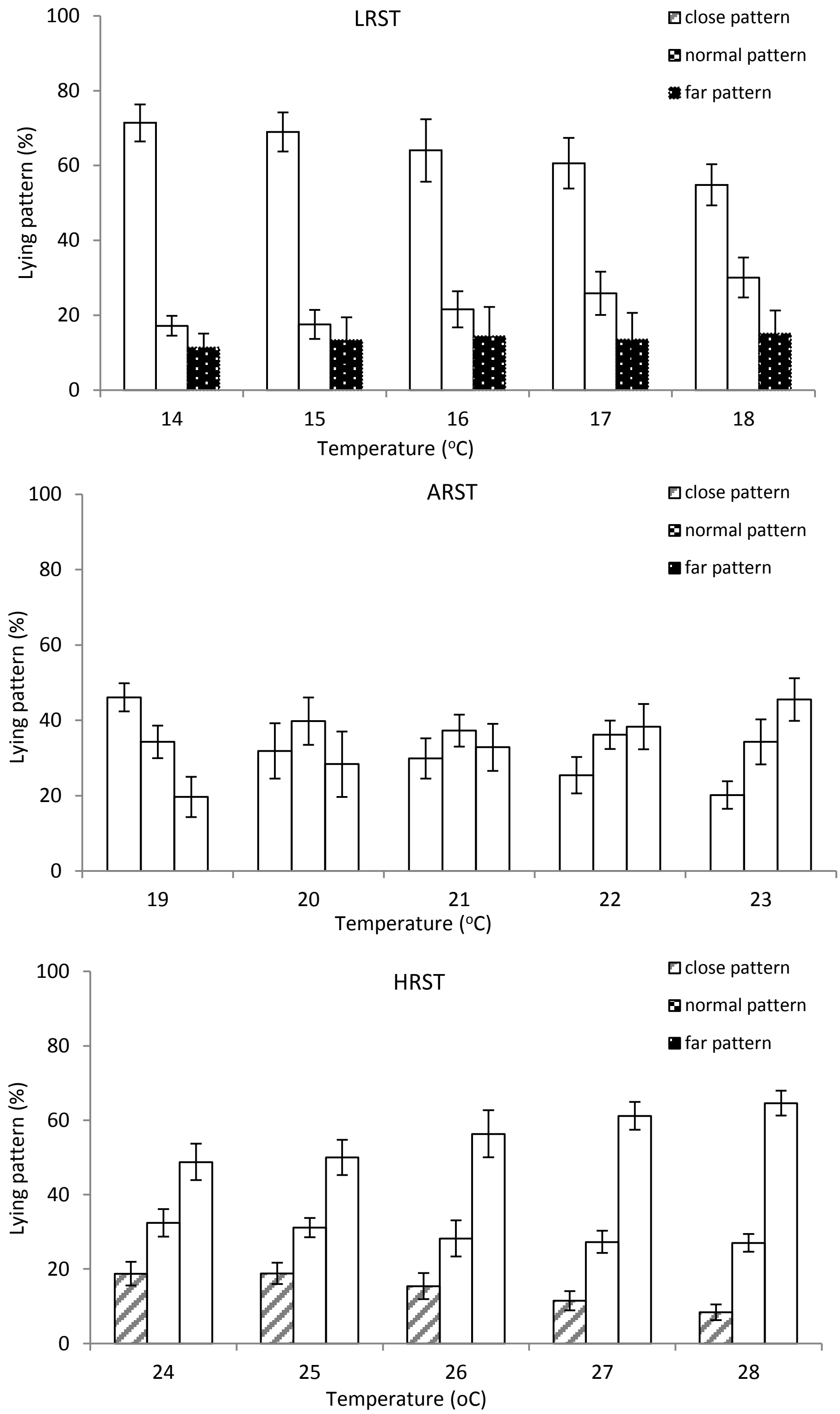


Figure 5.7- The three lying patterns for each thermal category allocated (mean % of Delaunay Triangulations (DTs) with their standard deviation (SD) bar). ARST= around the room set temperature, LRST= lower than the room set temperature, HRST= higher than the room set temperature.

Results of pig lying patterns, described through the image processing techniques and using the DT features, showed that in the LRST category pigs at the lowest environmental temperature (14 ^{o}C) adopted a body posture that minimised their contact with the floor and maximized contact with other pigs. As a result, the number of triangles with a perimeter of less than 200 pixels in the DT was higher, as a well as the percentage of close patterns. As the temperature increased in this category the number of huddling pigs declined, so the number of triangles with $P \leq 200$ pixels decreased.

Conversely, in the HRST category, where the temperature range was between 24-28 ^{o}C, pigs lay down with their limbs extended in a fully recumbent position and tried to minimise their contact with pen mates. The number of triangles with perimeter of more than 350 pixels increased and the percentage of far patterns was higher than other patterns. The maximum value for far pattern in this group happened when the temperature was at the highest level (28 ^{o}C), and the percentage of close pattern showed the lowest value in the study. This result is in agreement with other researchers (Shao and Xin, 2008; Costa et al., 2014) who have reported that in higher temperatures pigs tended to spread out and in a cold situation they tried to huddle or touch each other. In the ARST category, because the situation was around the room set point temperature, pigs had more side-by-side patterns (Riskowski, 1986; Shao et al., 1998) so that the percentage of triangles with $200<P<350$ pixels was higher in this category. It needs to be considered that the value of P obtained from the DT features for different lying patterns depends on the age and size of pigs, so more study is needed for generalization of the method and determination of the values of P in relation to the size and age of pigs.

5.3. Categorizing of lying patterns

Table 5.3 shows the average, maximum and minimum values, and SDs of the three extracted features (MVP, MVL_{max}, MVL_{min}) from each DT. According to the ANOVA results, the MVP, MVL_{max} and MVL_{min} differed significantly between thermal categories used in the ANN definition (all $P<0.001$). With the five temperatures in the range for the LRST category, the minimum value of each variable was observed in the lowest temperature (14 ^{o}C) while the maximum value was at the highest temperature (18 ^{o}C). Furthermore, the same tendency was obtained for the other two thermal categories. The results obtained for the described MLP network showed that the selected neural network was able to correctly classify lying behaviours with an overall accuracy 95.6 % according to the different thermal categories, and with satisfactory sensitivity (from 89.1 to 94.2 %), specificity (from 94.4 to 95.4 %) and accuracy (from 93.3 to 95.2 %), for the test set data (Table 5.4).

Table 5.3- Statistical data (average, minimum, maximum and SD) of the Delaunay triangulation features in different thermal categories.

	LRST			ARST			HRST		
	MVP	MVL_{max}	MVL_{min}	MVP	MVL_{max}	MVL_{min}	MVP	MVL_{max}	MVL_{min}
Ave	170.8	84.3	46.2	284.9	122.4	71.4	398.3	179.9	92.3
Max	250.6	126.1	73.3	340.9	162.4	98.2	460.8	230.7	120
Min	138.1	57.4	30	208.2	85.2	44.2	336	120	70.4
SD	25.1	14.1	9.1	31.8	13	7.8	33.9	27.3	11.5

ARST= around the room set temperature, LRST= lower than the room set temperature, HRST= higher than the room set temperature. MVP= mean value of perimeter, MVL_{min} = mean value of minimum lengths, MVL_{max} = mean value of maximum lengths, Ave= average, max= maximum, min=Minimum. All measures (MVP, MVL_{min} and MVL_{max}) differed significantly between temperature categories ($P<0.001$)

Figure 5.8 presents the ROC curves for individual thermal categories, comprising both the sensitivity (equivalent to true positive rate) and complement of specificity to unity (equivalent to false positive rate). The AUC values obtained were 0.98 for the LRST, 0.96 for the ARST and 0.98 for the HRST test sets. The value of AUC represents the discrimination ability of a classifier (Grzesiak et al., 2010) and the value for a realistic classifier should be more than 0.5, with the AUC range between 1 (best separation between the values) and 0.5 (no distributional differences between values) (Fawcett, 2006).

It is generally difficult to develop a simple linear model to predict data with overlapping categories. Thus, all three mentioned variables of the DT were assigned in the MLP network to identify the three thermal categories. As can be inferred from Table 5.4, the HRST category showed the lowest value of precision for the test dataset, in which sensitivity was 89.1%, specificity was 94.7% and accuracy was 93.3%, while the values obtained for LRST were 94.2%, 95.4%, 95.2%, respectively. Shao et al. (1998), who studied classification of swine thermal comfort using feed-forward network and binary image features (i.e. Fourier coefficients, moments, perimeter and area, combination of perimeter) in laboratory conditions (4 chambers and 10 pigs per chamber), obtained values of correctly classified samples of 78, 73, 86 and 90% for the test sets.

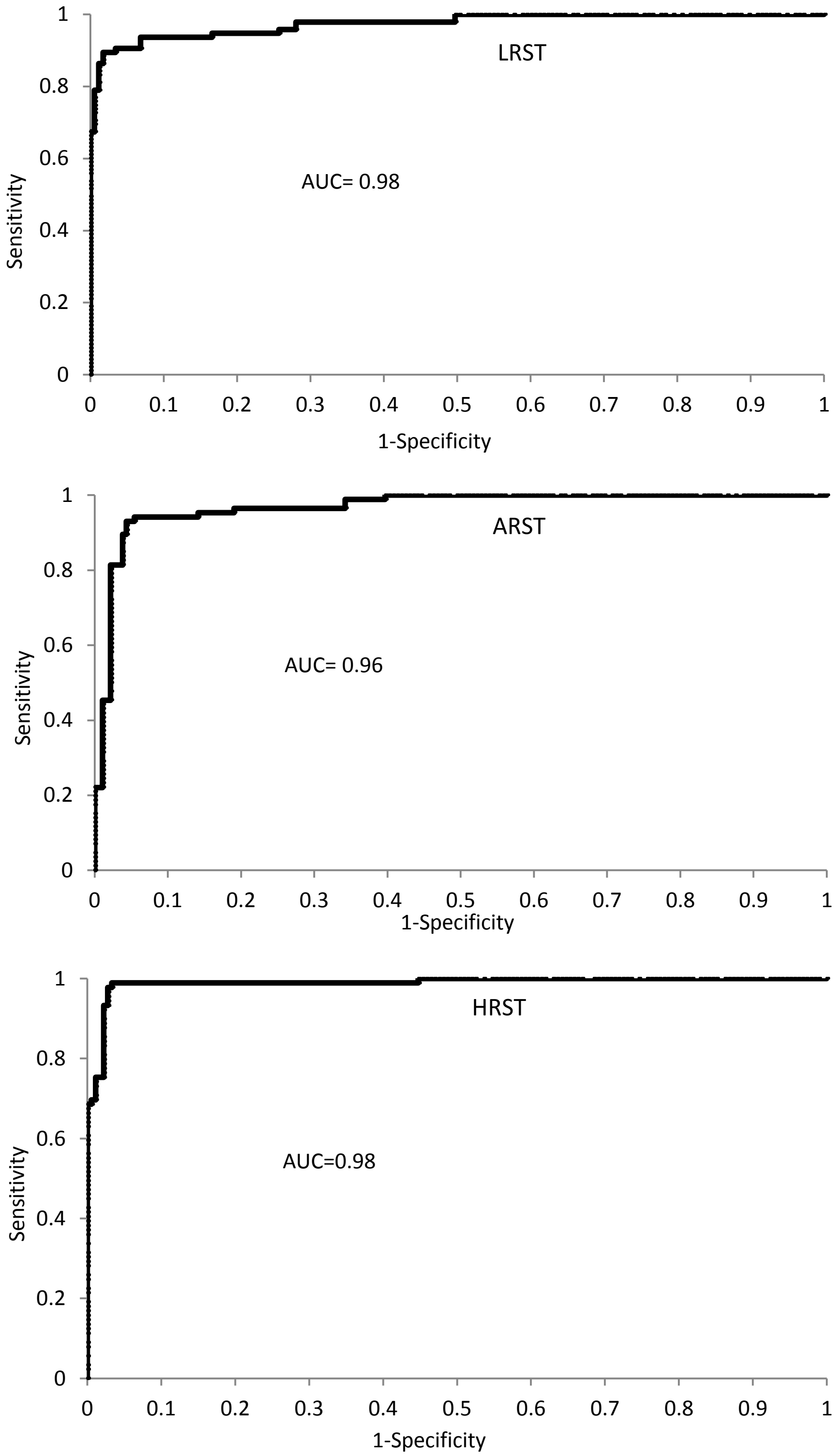


Figure 5.8- The relative operating characteristic (ROC) and the area under curve (AUC) values of network test set. ARST= around the room set temperature, LRST= lower than the room set temperature, HRST= higher than the room set temperature.

Computing the mentioned binary image features in a commercial pig farm, with different pen structures, may increase the error of classification; for instance some pigs tend to lie close to the walls which makes the area or perimeter results inaccurate. Therefore, using a method for finding the centre of each pig and applying a precise mathematical model, the method used in this study, could increase the classification precision. In this study, the lower performance of ANN classification in HRST might be explained by the fact that, in higher temperatures, pigs increase the space they occupy and normally move to cooler places like the dunging area (Spoolder et al., 2012). As a result, the DT extracted features could change more than in the usual situation. Furthermore, in the LRST condition, they huddle together more in an area which appears warmer to them and the network could classify with better performance by using arranged DT features (Table 5.4).

Table 5.4- The ANN analysis: sensitivity, specificity and accuracy for the test dataset.

Thermal category	Group data		
	Sensitivity	Specificity	Accuracy
LRST	94.2%	95.4%	95.2%
ARST	90.6%	94.4%	94.3%
HRST	89.1%	94.7%	93.3%

ARST= around the room set temperature, LRST= lower than the room set temperature, HRST= higher than the room set temperature.

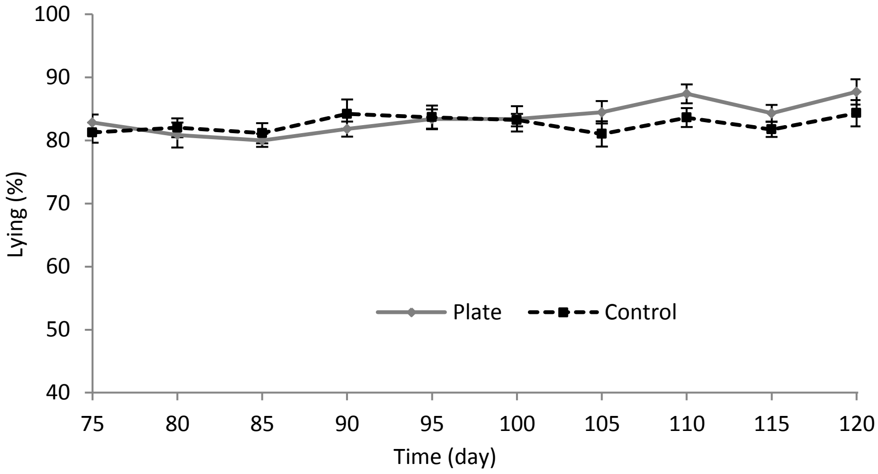
Developing a classifier with high performance could be a basic step for creating an automatic monitoring system for enhancing pigs' welfare and, if the controller system of the environmental conditions can be based on the comfort behaviour of pigs, better welfare may be achieved (Shao et al., 1998). The technique presented in this study allows classification of lying behaviour using an ANN on the basis of the DT features. Since the experiment was run for a period of only 15 days, in pens with the same size and shape, the change in size of the pigs during this period was not great. Thus, further research is needed to model pigs with different sizes across a whole production batch, and pens with different structures should be considered in the model before making the method practicable for pig farms. The major advantage of applying a high performance classification system in commercial farm conditions is that the changes of lying behaviour in the different thermal categories, which mainly rely on the room set temperature, could be used in an automatic and continuous way with a large number of pigs and pens in non-laboratory situations. Changes in environmental temperature in pig farms result in alterations in body heat transfer and cause energy and meat production losses, so using an automatic image analysis and precise mathematical method can provide a less stressful situation for pigs and workers, and benefit economic outputs.

In the current study, the ventilation system in use was not capable of maintaining the room at a temperature around the set point temperature for periods in both cold and warm seasons. This illustrates the need to design more appropriate ventilation systems in commercial practice. However, a single room set point may not be the most appropriate for animals in different situations. Knowing the lying pattern of the pigs gives the possibility for farm managers to select the best room set temperature regarding their own animals and farm conditions. Connecting the proposed monitoring system to the room ventilation and potential heating or cooling system will be worthwhile to deliver better performance in an automated farm management system. As a result, more economic outputs and better animal welfare may be achieved.

5.4. Lying behaviour monitoring after enrichment substrate provision

Direct vision and video scoring of pig lying behaviours are popular methods in pig welfare monitoring, however these are time consuming methods (Stukenborg et al., 2011). A computer based approach was chosen to find the lying position and pattern of groups of pigs when providing an enrichment rooting material in a commercial farm situation. To validate the image processing technique 4000 images (10 days × 2 replicates × 200 images per day) were analysed, which is around 25 % of the total number that were used in this study. The number of fitted ellipses (pigs) in each selected image after applying the image processing algorithm was counted and then compared to the number of pigs in that image with reference to manual labelling.
Using machine vision techniques, the lying position of pigs in different zones could be automatically calculated. In total, 17280 images were separately analysed (10 days × 144 times in a day × 6 pens × 2 replicates). Results of the validation study on ~25% of the images showed that the average percentage of frames with correct estimation of pigs in the control pen and plate treatment pen using the image processing technique was 95 and 93%, respectively. Incorrect estimations occurred when the algorithm wrongly considered other objects in the pen as pigs or failed to truly localize them. This was most often due to a reduced image quality when flies covered the camera lens with dirt over time.

The percentages of lying pigs in 10 min intervals for the plate and control pens are shown in Figure 5.9. The percentage of lying pigs increased during the period of the experiment for both the plate and control pens. Statistical analysis showed that there was a significant effect of day on overall percentage of lying ($p<0.001$), with lying time increasing with age, but no difference between the treatments or treatment × day interaction.



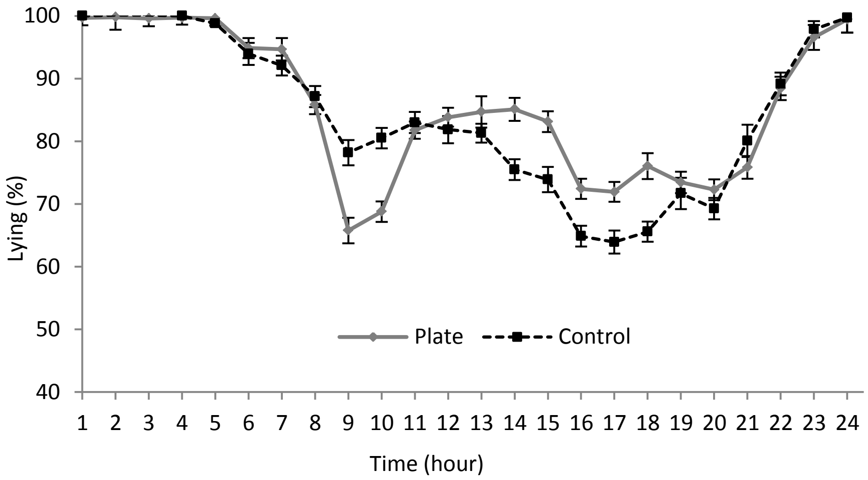


Figure 5.9- Pig lying frequency during 10 separate days at 5 day intervals over the fattening period (left), and over the 24 hours of the day (right) in pens provided with daily maize silage substrate onto a plate or control pens with a hanging toy enrichment along with standard errors.

As shown in Figure 5.9, between midnight (12 AM) and early morning (6 AM), which was the first feed delivery time, almost all pigs were lying. The lying percentages were reduced from 6 to 9 AM by delivery of fresh feed in both treatments, and further reduced in plate pens because of delivery of rooting material between 8 and 10 AM; on average, around 65% of pigs were lying pigs in these pens while in control pens this value was about 80%. In both treatments, a second activity peak was apparent in the late afternoon and was more pronounced in the control pens. There was a significant treatment × time (hour) interaction indicating that pigs of different treatment had different lying behaviours during the 24 h ($p<0.001$). Table 5.5 shows the results of statistical comparison of the effect of treatment on the lying pattern of grouped pigs. Whilst provision of rooting material had no significant effect on the overall time spent lying by the pigs, it did influence lying location.

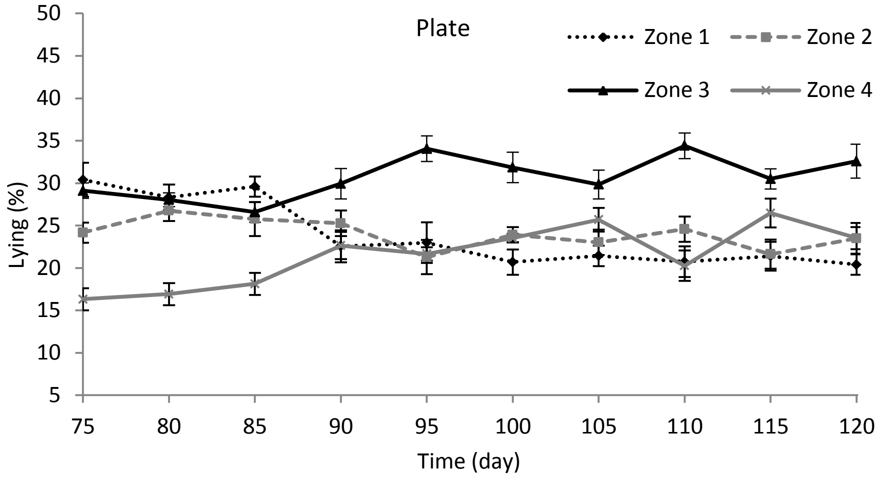
Table 5.5- The effect of rooting material provision onto a plate on the total lying time of pigs and the percentage of lying animals in different pen locations.

	Treatments (mean value)		SEM	F Value	P-value
	Plate	Control			
Total lying (%)	85.73	84.74	0.871	0.39	0.565
Zone 1 (%)	23.68	30.93	0.817	38.23	0.003
Zone 2 (%)	24.33	21.83	0.952	3.44	0.137
Zone 3 (%)	30.64	22.26	0.594	65.1	0.0006
Zone 4 (%)	21.39	25.01	0.866	8.39	0.044

SEM= standard error of the mean

The general activity patterns of the animals were in accordance with published literature. The proportion of pigs lying showed an increasing trend over time, which is in line with previous findings that lying time increases with age (Ekkel et al., 2003). Furthermore, when looking at the effect of time of day, pigs showed a typical bi-phasic pattern of activity, with morning and later afternoon activity periods as reported elsewhere (Zwicker et al., 2012; Lahrmann et al., 2015). However, the results illustrate that the pattern of pigs' activity during a day was altered by delivery of a rooting substrate, in agreement with Bolhuis et al. (2010) and Fraser (1985). The presentation of an attractive and novel substrate stimulated activity while this remained present, but animals then showed more lying behaviour later in the day, possibly as a consequence of gut fermentation effects of the ingested material (Bolhuis et al., 2010).

The percentage of lying pigs in each zone during the experiment is shown in Figure 5.10. In the control pens, the majority of pigs chose to rest in zone 1, the designated lying area, but as the pigs aged and became larger, the percentage of lying pigs in zone 1 declined and the occurrence of resting in other pen areas increased. In plate pens, the proportion of pigs resting in zone 1 decreased more markedly over time, whilst an increasing proportion of pigs chose to lie in zones 2 and 3, adjacent to the plate.



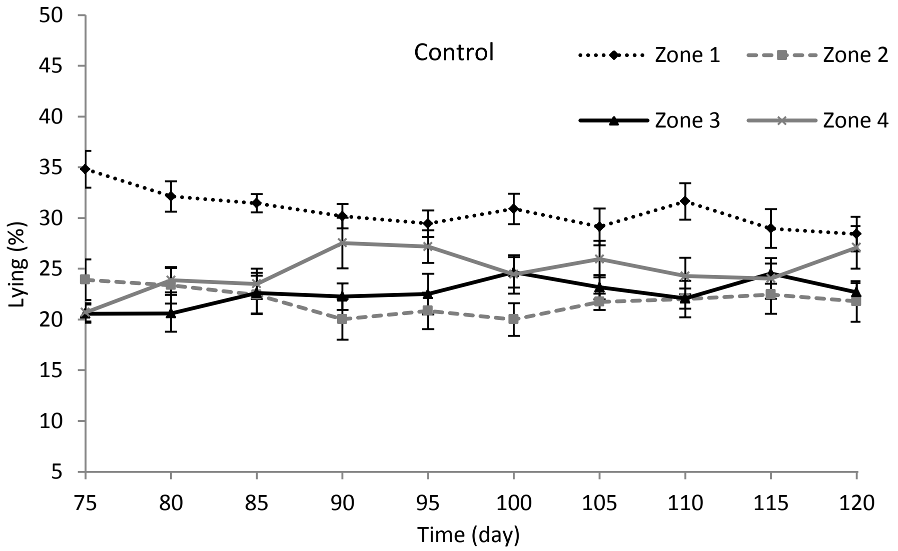


Figure 5.10- The percentage of lying pigs located in different regions of the pen during 10 separate days at 5 day intervals over the fattening period in pens provided with daily maize silage substrate onto a plate (top) or control pens with a hanging toy enrichment (bottom) along with standard errors.

The mean value of the percentage of lying pigs of each zone across the 24 h period is shown in Figure 5.11. Control pens showed a consistent pattern of pen use across the day. In contrast, the pens equipped with plates showed a change in the preferred zones in the hours immediately following substrate provision, when they reduced resting in the region of the plate, reverting back to their original preference once substrate related activity was over.

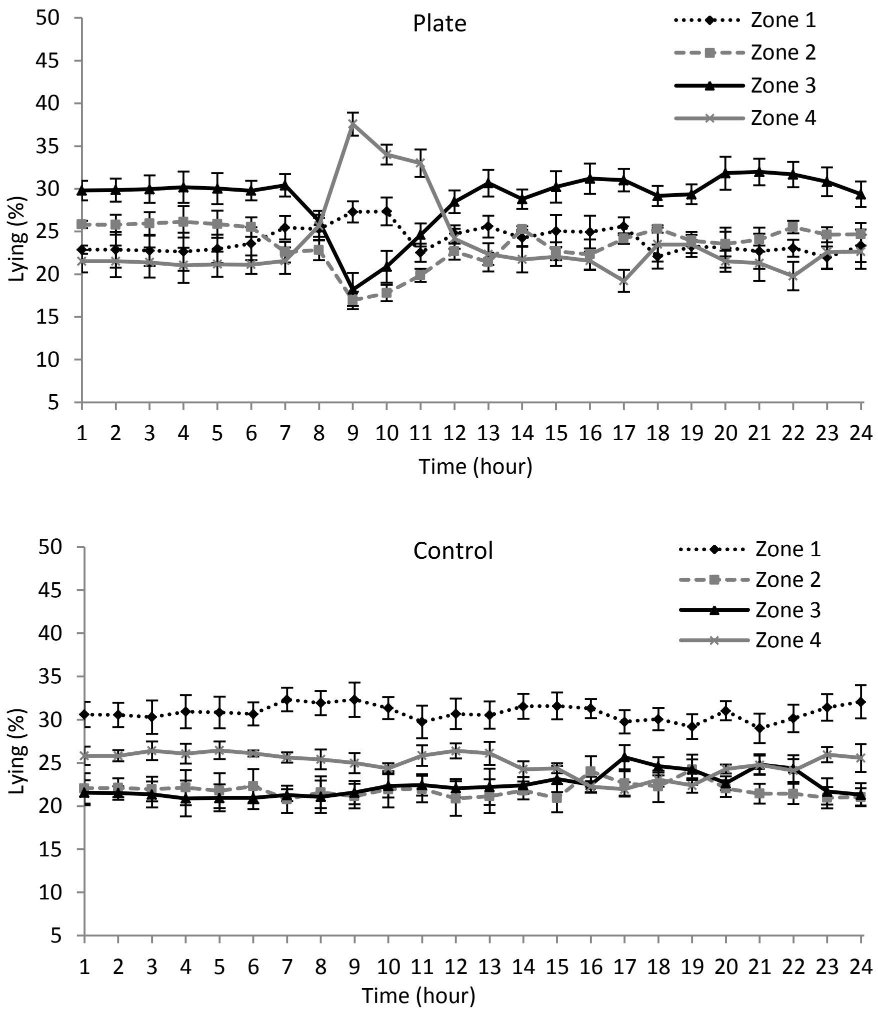


Figure 5.11- The percentage of lying pigs located in different regions of the pen over the 24 hours of the day in pens provided with daily maize silage substrate onto a plate (top) or control pens with a hanging toy enrichment (bottom) along with standard errors.

Treatment significantly affected the spatial distribution of the lying pigs. Control pigs showed a consistent preference for lying in zone 1, the designated lying area, and later as they increased in size also in zone 4. Although this was the designated dunging area, the choice to lie there might reflect the preference of animals to lie against pen walls rather than in open areas. In contrast, pigs in the plate pens changed their preferred lying area according to the time of day, avoiding the plate zone during the period of substrate-induced activity, but then showing more lying in zones 2 and 3 across the rest of the day. The avoidance of resting in an area of activity is to be expected (Olsen et al., 2001). Since the amount of rooting substrate delivered in this experiment was limited, and it had largely disappeared after 2-3 hours, the effects on focussed activity and inhibition of resting were intense but transient. However, current legislation states that enrichment should be permanently available, raising the question of whether a greater quantity of rooting material lasting throughout the day would cause less intense disruption or give rise to long term relocation of the preferred resting area. The reason for choice of the zones in the vicinity of the plate for subsequent resting in the current experiment is less obvious. It is possible that, since the plate was the only area of solid flooring in the pen, pigs might be attracted to lie there for this reason (Aarnink et al., 1996; Savary et al., 2009), with social facilitation resulting in other pigs subsequently joining this resting group. Further work with different flooring types would be necessary to further investigate this issue.

The lying zone which pigs choose is determined by a number of factors, including design of the pen, location of feeder and drinker, and environmental conditions relating to temperature, air velocity and humidity (Spoolder et al., 2012). Lying in the dunging area has negative consequences for hygiene and thermoregulation, and results in dirtier animals (Spoolder et al., 2012). This study illustrates how automatic monitoring of animals can be a useful tool for researchers and for farmers, allowing low cost monitoring of pigs lying behaviour which can be used as an indication of the way in which environmental conditions affect their welfare and health.

5.5. Mounting event detection

Following image capture and processing, the relative distances between individual pigs were estimated. Figure 5.12 shows the how the Ed between two points (H/T, H/S of one pig to another one) changed in successive frames; it could be inferred that the distances between the mounting and mounted pig declined before the mounting event happened. The algorithm only detected an Ed less than 43 (in pixels) (Figure 5.13) as the ROI in this study. Figure 5.13 illustrates the changes in Ed before and after the ROI for a mounting behaviour has been identified; when the Ed=0 the mounting events happened (for period of 5-14 s, 17 s, 27-33 s and 35 s) and it can be seen that there was a discontinuous mounting event. The major axis length of the fitted ellipse for both mounting and mounted pigs for a mounting event which happened from behind is shown in Figure 5.14. According to the diagram, the length of each pig was around 80 (pixels) (see Table 5.6) and, as the mounting event happened at second 5, the algorithm considered the mounting and mounted pigs as one pig and fitted an ellipse with a bigger major length. At the beginning of the mounting event, the length of the major axis was greater and it then declined over time as the mounting pig demonstrated pelvic thrusts (Hintze et al., 2013). Figures 5.15 and 5.16 illustrate the major and minor axis length of mounting and mounted pigs when the mounting event occurred from the side. Here, the major length during the mounting event was around 1.4 pig lengths, while the major axis length in the mounting event was approximately 2 times one pig's minor length.

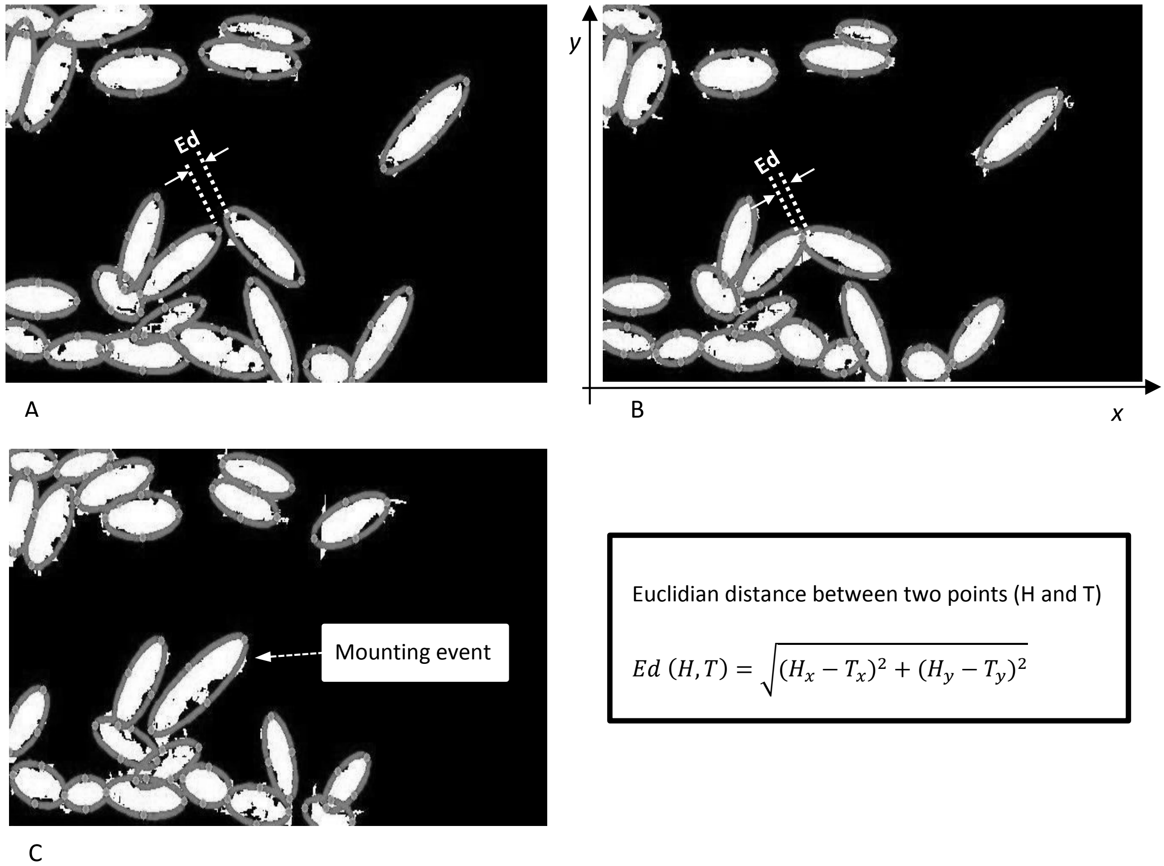


Figure 5.12- The Euclidean distance (Ed) between Tail and Head of two pigs during a mounting event. For a mount from behind: (A and B) the Ed declined, (C) mounting happened from the back giving a bigger ellipse.

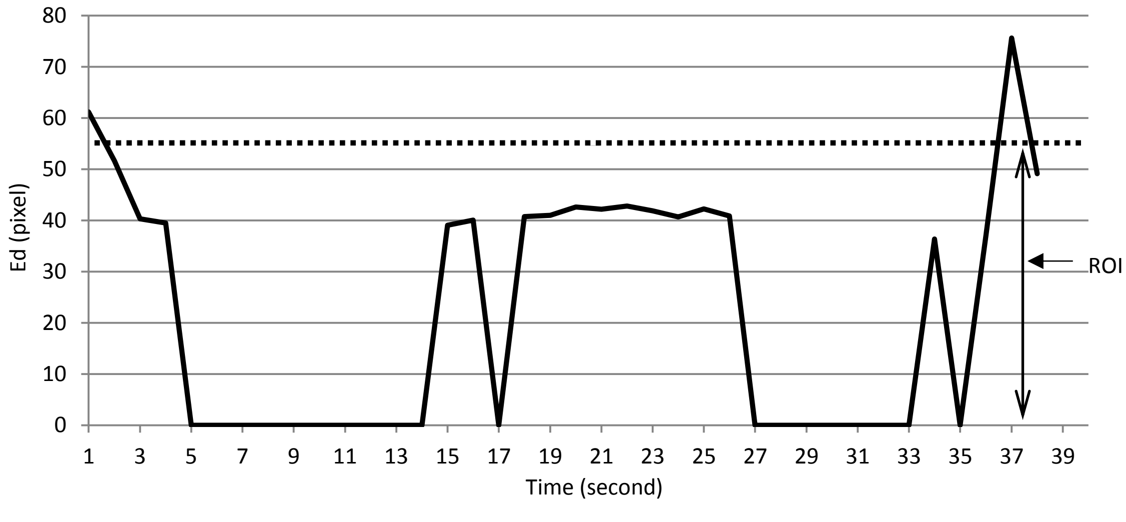


Figure 5.13- The Euclidean distance (Ed) between two pigs (mounting and mounted) and the region of interest (ROI).

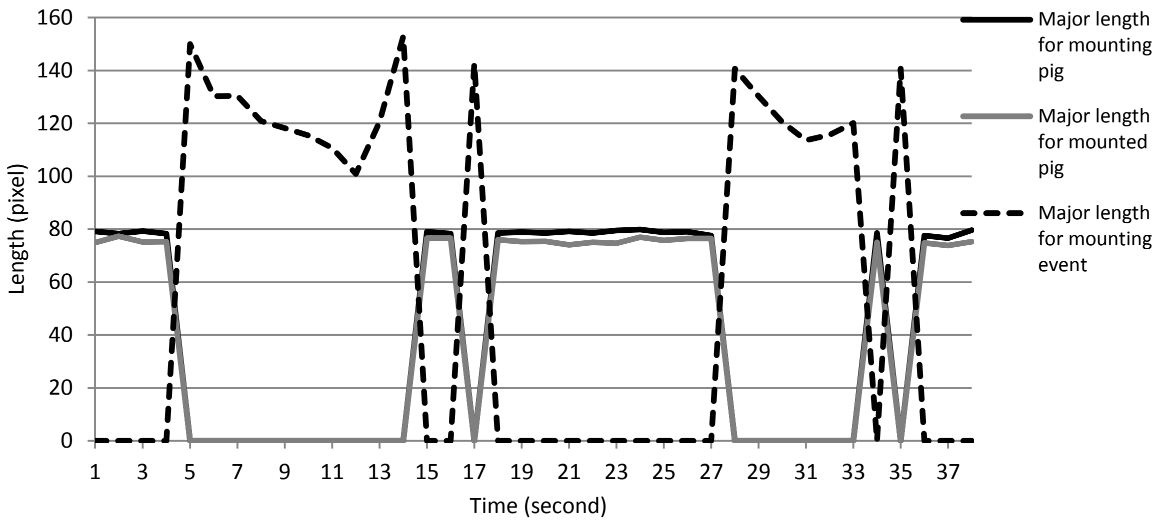


Figure 5.14- The major axis length of mounting and mounted pigs, along with the mounting event length, for a mounting event from behind.

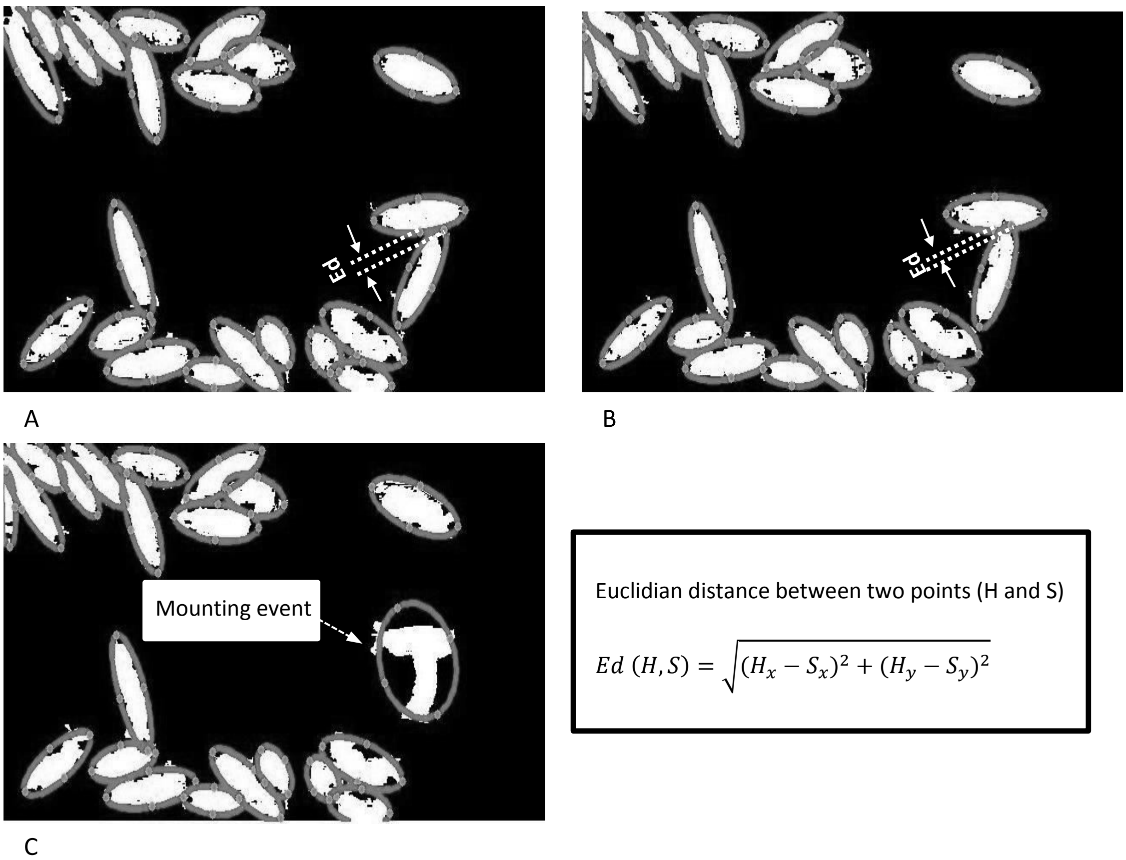


Figure 5.15- The Euclidean distance (Ed) between Tail and Head of two pigs during a mounting event. For a mount from the Side: (A and B) the Ed declined, (C) mounting happened from the side giving a bigger ellipse.

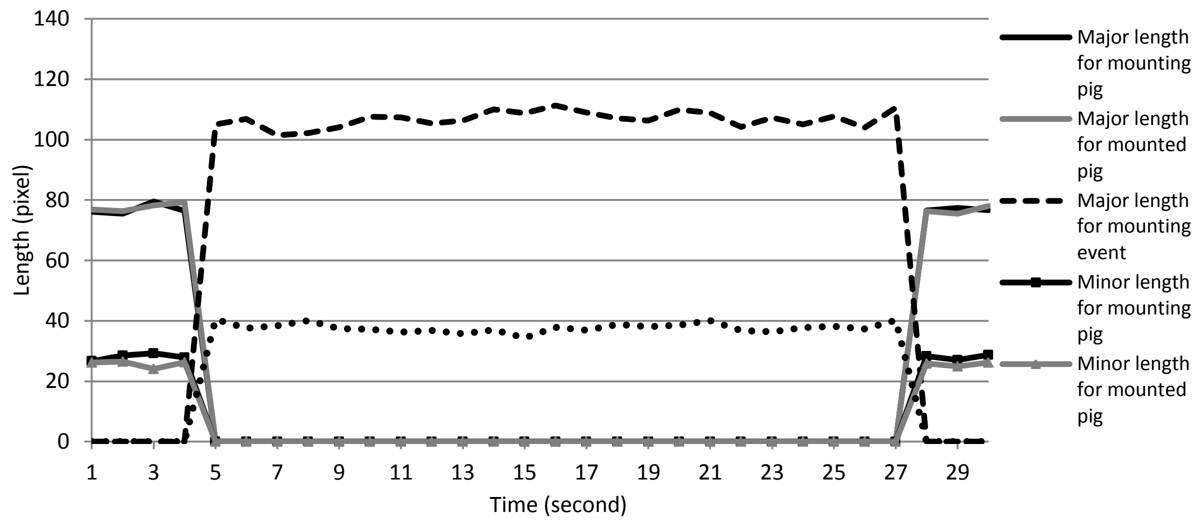


Figure 5.16- The major and minor axis length of mounting and mounted pigs along with mounting event length, for a mounting event from the side.

Table 5.6- Mean and standard deviation (SD) of major and minor axis length of pigs in region of interest (ROI) before and after a mounting event.

Time (second)	1	2	3	4	27	28	29
Major axis length (pixel) ± SD	76.4±0.5	75.8±0.6	77.8±0.4	76.8±0.6	76.4±0.2	76.9±0.6	77.3±0.9
Minor axis length (pixel) ± SD	26.4±0.3	27.4±0.8	27.3±1.1	26.7±0.6	26.5±0.9	25.9±1.2	27.1±0.9

From the 200 h of recorded videos, a total of 120 mounting events were visually obtained. In general, 1800 s of mounting events and 7,200 frames (4 frames per second) were obtained from both pens during the study. The mounting events were manually validated from the recorded video frames by an expert. The validation scales used for finding the performance of the detection system were defined as in Table 5.7 (Firk et al., 2002; Pourreza et al., 2012; Tsai and Huang, 2014).

Table 5.7- Definition of validation parameters.

Scale	Definition	Value
TP	Mounting event considered as mounting event	4753
FP	Non-mounting event considered as mounting event	247
TN	Non-mounting event considered as non-mounting event	1925
FN	Mounting event considered as non-mounting event	275

The results obtained from the validation of the algorithm show a good mounting detection rate with satisfactory sensitivity (94.5%), specificity (88.6%) and accuracy (92.7%). According to the criteria of Table 5.7, some mounting frames were not recognized and there were some false positives. These errors sometimes occurred due to limitation in the pen structure where there was a water pipe in the middle of each pen (2.5 m from the floor) and some mounting events happened in this invisible area. Furthermore, when the apparent mounting event happened near a pen wall and/or when the mounting pig contacted or tried to contact a pig from a neighbouring pen, drank from the attached nipple drinker or licked the wall (Hintze et al., 2013), and due to the low image quality, the system could not properly distinguish the wall and pigs.

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \longrightarrow \frac{4753}{4753 + 275} = 94.5\% \quad (5.8)$$

$$Specificity = \frac{TN}{TN + FP} \times 100 \longrightarrow \frac{1925}{1925 + 247} = 88.6\% \quad (5.9)$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \longrightarrow \frac{4753 + 1925}{4753 + 247 + 1925 + 275} = 92.7\% \quad (5.10)$$

It is clear that the mounting behaviours in pigs need different detection methods from those of some other species due to differences in the nature of their behaviours. For example, the mounting behaviour in cows contains a few seconds of following behaviours (Tsai and Huang, 2014), in which the mounting cow closely follows the mounted cow, and then a jumping or mounting event happens. Tsai and Huang, (2014) have shown that, because of following behaviours in cows, using the motion analysis of mounting events could be a good technique for mounting detection. In contrast, mounting in the pig often happens without any preceding following. Furthermore, the mounted pig may be sitting down or moving away during the event, so using the recommended method for cows may not be applicable in pig behaviour detection.

This study has shown that binary image and fitted ellipse features can be used to extract features related to mounting behaviour among pigs. However, the system could not identify all mounting events, because the CCTV camera could not always detect the pig's body and make a clear distinction between pigs and wall or pigs and background (pen). This problem might be overcome by using 3D image data (i.e. TOF, Kinect depth sensor) which has the advantages of eliminating errors related to animal colours, background and different ambient lighting (Kongsro, 2014), animal body detection in more detail (Weber et al., 2014) and pictures with higher resolution. However, using expensive cameras with better colour and object detection in commercial farms, in an environment with high levels of humidity, dust and ammonia, and their associated detrimental effects on electronics, may not be economically acceptable for farm managers. So, possibilities for improving the algorithm for images from simple CCTV cameras or using other methods need to be considered in future research.

To date, no previous studies have been carried out to automatically detect pig mounting behaviours. The technique proposed here can automatically detect mounting events among pigs, even in commercial farm conditions. The method could be a valuable tool to aid farmers to increase animal welfare and health, and reduce injuries and economic losses, particularly as the use of entire males becomes more common. As the pigs grow larger, the mounted pigs may have increased risk of injury (Clark and D'Eath, 2013), and may be mounted more frequently by other pigs. So, with accurate information about the mounting events, the farmer can move quickly to address problem pens or seek interventions. Additionally, automated tracking of the time course and frequency of mounting behaviours within pens could facilitate the work of researchers exploring methods of prevention or alleviation of this behavioural problem.

6. General discussion

The main objective of the present study was to develop an automated computer vision based system for monitoring behaviour of groups of pigs. The developed machine vision approaches and the results of the study have been presented. The image processing and the ANN algorithms were developed in MATLAB® software and tested in a commercial pig farm in Stafford, UK. The video recording methods presented in this research were based on a top view capture system in the pig barn due to the simplicity and robustness of top view monitoring systems for implementation in field conditions (Van der Stuyft et al., 1991).

The present research was focused on developing automatic monitoring systems which can be applicable for commercial situations by using cheap CCTV cameras. Various technologies, such as animal-borne sensors, are now available and applicable for monitoring pig or sow behaviours, i.e., feeding, drinking or lying behaviours. However, the advantages of camera based monitoring systems can be named as: no physical contact with the animal, cheap in large scale application, no pain for animals (such as insertion of ear tags), less stress and no negative hygiene consequences for either animals or farmers. Improving digital camera quality, remote data transfer systems and modern computer technologies provide many opportunities for researchers and business owners to work more on automation in livestock husbandry.

In this research it was first explored how lying behaviour of group-housed pigs in a commercial situation could be characterised in a fully automated system. One of the most important factors affecting welfare throughout the stages of breeding, growth and maturity is the environment in which animals are maintained. Environmental factors provide important information for the better management of pig farms and they have significant effects on pigs' production efficiency, health and welfare. Due to the physiological and morphological limitations on thermoregulation of pigs, they change their lying behaviour to adapt to high and low temperatures. In hot conditions they avoid physical contact with others in the pen during resting time, while at low ambient temperatures they will huddle together with more physical contact (Hillmann et al., 2004; Spoolder et al., 2012). Conventional observation which is based on direct or recorded video observation has been made in numerous studies. This monitoring approach has its own limitations due to time requirement and has the possibility for subjective interpretation and hence observer bias (Tuyttens et al., 2014). This was the first time that group lying behaviours could be detected precisely thanks to image processing and the DT method. The methodology used was based on ellipse fitting models to identify the location of each animal. Since each single pig in the image is similar to an ellipsoidal shape, the *x*–*y* coordinates of each binary image could be used for ellipse fitting algorithms to localize each pig (Kashiha et al., 2014a and 2014b). Fitting an ellipse to each animal simplified the model details in comparison with more precise perimeter measurements because projecting body parts (limbs) were ignored. The principles of such a model are independent of type of animal and potentially can be tested for application to other livestock. Different parameters of each ellipse were found to help in distinguishing animal from background, and also from other animals, to provide useful information for behaviour analysis. These parameters included the centre of ellipse (or centre of pig's body in top view image), a major and minor axis giving an orientation to the fitted ellipse (Kashiha et al., 2013a).

One of the possible applications of the proposed lying behaviour detection method is to characterise group lying patterns in relation to environmental temperature. A methodology was developed which employs a DT model to obtain the distance between different pigs in the group during the lying time, and it was demonstrated that this was sensitive to detect changes in lying behaviour in different room temperatures. Information on the lying pattern of the pigs reflects the perception of thermal comfort of the animals themselves and gives the chance to the farm manager to select the best room set temperature regarding their own animals and farm conditions. Defining different lying patterns, based on the extracted DT features from the group lying patterns of pigs, could therefore help farm managers to assess the adequacy of thermal provision for pigs in large scale farms. Use of the MLP classifier network made it possible to classify the thermal category in a room using the DT features without need for human interpretation. The ability to generate rapid categorisation of environmental adequacy means that such data could be used as an input for ventilation system management. The frequent fluctuations in external air temperature make barn ventilation management difficult. Room temperature in a building for growing pigs is normally kept within their thermal comfort zone (at around 20 ^{o}C), and the conventional measuring systems in commercial pig farms are based on some air temperature sensors (one or two) at fixed points above pig level (Mendes et al., 2013). This system cannot respond quickly to climate changes in some cases, so finding a method which indicates the thermal experience of the pigs themselves by image processing could be a first step to improve control of the ventilation system for better thermal comfort and welfare of pigs in the room. By connecting the proposed monitoring system to the room ventilation control system, it could be possible to deliver better animal performance and welfare in an automated farm management system.

Another application of the proposed method is automatic and continuous monitoring of location of pigs in a pen during the lying time by finding the *x-y* coordinates of each fitted ellipse in the image. This provides an impression of how group pigs spend their lying time in relation to their resting, dunging or feeding zones. Such information is important in assessing the adequacy of pen design and management, and has important implications for pen hygiene. For example, lying in the dunging area has negative consequences for pig's hygiene, resulting in dirtier pigs and pens (Spoolder et al., 2012). At a time when there is public pressure to reduce antibiotic use and presence of zoonotic organisms in animal products, maintaining a hygienic environment which will help to prevent subclinical disease is becoming increasingly important. Furthermore, changes to established patterns of pen use, or instability in functional areas, may be a precursor to behavioural problems such as tail biting. Early warning of such risk would allow farmers to implement appropriate interventions to avert the problem. Allowing pigs to express behavioural elements like feeding and exploring by providing rooting materials can improve their welfare (Bracke et al., 2007; Vanheukelom et al., 2012), reducing the level of aggression, the biting of tails, ears and other body parts among pigs (Day et al., 2002; Van de Weerd et al., 2006; Zonderland et al., 2008; Jensen et al., 2010). In this research, the application of the proposed image processing technique was also demonstrated for automatic monitoring of pigs lying behaviour (time and position changes) when enrichment material was distributed into pens. Automated image processing techniques now give the potential to carry out behavioural research in a more effective way (Nasirahmadi et al., 2017a). This study shows that machine vision can be used as a precise and rapid method for quantifying pig lying behaviour for research or practical applications.

The research has demonstrated how image geometrical (ellipse) features could also be utilized to monitor mounting events amongst group-housed pigs. Mounting events amongst pigs can increase the risk of bruises and damage to the skin, and lameness or leg fractures (Rydhmer et al., 2004; Faucitano, 2001; Harley et al., 2014). These injuries and the general unrest in the group can have considerable negative economic consequences (Rydhmer et al., 2006). To control risk of boar taint and undesirable male behaviours European countries are castrating piglets which is a painful and stressful event (Prunier et al., 2006; Hintze et al., 2013). This research was the first explored how mounting behaviour of group-housed pigs could be detected by employing an automated machine vision method. Based on the ellipse features and the Ed between head/tail of one pig to head/tail of other pigs, the behaviour can be deduced through images extracted from the CCTV cameras. Comparison of image processing measurement with visual observation illustrated that mounting events could be measured in real-time with a high accuracy by using the ellipse fitting technique and mathematical approaches. The results show that the model is accurate enough to monitor the behaviour among pigs and issue alerts which could be used by farmers to intervene when this behaviour becomes frequent enough to affect welfare and performance. Furthermore, the principals and the developed algorithms could be used for automatic mounting behaviour detection to detect returns to oestrus in group-housed sows. Additionally this could be used in other species, such as cattle, to achieve successful detection of oestrus signs. In cattle, where poor fertility is a major problem, detecting the signs of oestrus is very important for reproductive success and economic efficiency of a herd.

As described in this research, a camera as a single sensor could be utilized to monitor many different variables in livestock farms. To use this monitoring system, the farmer will need to install only one sensor (camera) to collect extensive information on animal behaviour relating to the welfare status of a group of animals. This is more efficient than using devices on individual animals, such as application of RFID tags. Although the two technologies could also be used in combination, with RFID for monitoring of feeding and using cameras for the group monitoring of thermal behaviours which, together with thermal data of the animal barn (from temperature sensors), could be used in controlling the room ventilation system. However, it needs to be indicated that, despite the mentioned advantages of automatic machine vision monitoring systems, some environmental parameters such as dust, dirt, flies and moisture can lead to failure in the image acquisition system. These practical constraints require further attention if system failures and consequent economic losses are to be avoided.

In addition to its commercial applications, the use of an automated computer vision based system for monitoring animal behaviour also has many potential research applications. Most behavioural studies to date have involved video recording approaches (e.g., Scott et al., 2006; Jensen and Pedersen, 2007) which require a great deal of time and effort to score animals' activity or lying behaviour. However, in this research an automatic monitoring system which employs an ellipse fitting method has been demonstrated to be effective to monitor lying behaviour changes after daily maize silage provision into the resting area of pigs. This technique can help to rapidly and objectively monitor a large number of animal groups in studies designed to improve animal welfare by manipulating lying position and daily activity levels. Hence, there are many possibilities for application of this technique to benefit animal monitoring, not only for pigs but also for other livestock when testing a range of housing and management interventions.

7. Current limitations and future research needs

The automatic monitoring of animal behaviours by machine vision techniques has its own limitations in commercial farms compared to controlled conditions. The cost of cameras and sensors is an essential parameter for the farm owners; as a result more efforts need to be carried out for developing algorithms which work with cheap cameras and low quality images. The issues addressed in this study were only examined in one farm, so the reliability of the system needs to be more examined in a wider range of environmental situations.

One of the current challenges in commercial pig farms is control of the building ventilation system across a range of different outdoor climatic conditions to improve animal welfare and optimize energy usage. More efforts are needed to develop camera-based real-time control systems which allow animal-based input parameters. However, better solutions for environmental challenges like flies, which can cover camera lenses with dirt and reduce visibility, need to be investigated before a fully automated machine vision technique can be implemented in commercial pig farms with low maintenance input. Furthermore, the monitoring systems working in pig farms can be subject to other changing and challenging ambient situations (e.g. temperature, moisture, dust and light changes) and thus require a higher degree of flexibility and wider range of operation than generally taken into account by the previous studies.

This work focussed on application of cameras for the monitoring of animal behaviours. However, the combination of machine vision and multi-sensor approaches to record environmental changes may lead to improved performance of problem detection, since further sensors could compensate for some limitations of image distinction of machine vision systems. For instance, simultaneous application of acoustic sensors for recording animal vocalisations could make animal welfare assessment more accurate. Furthermore, there are major practical challenges in automation of individual livestock monitoring. Individual animal identification can be achieved using radio frequency tags which give greater reliability than image analysis due to the various uncontrolled conditions in indoor and outdoor farm environments, in combination with the fact that the animals in a group (i.e. cattle and pigs) can be highly similar in shape, colour and size. Fixed cameras also have a limited field of view, making them less practical in more extensive livestock systems. However, other imaging systems like drone-mounted cameras, which are widely used in tracking of wild animals in different outdoor situations, might also be applied for tracking of extensively kept livestock. For such further development of the technology, different feature detection algorithms e.g. Scale Invariant Feature Transform (SIFT), Speeded Up Robust Features (SURF), Haar-like and machine learning approaches are essential (Olivares-Mendez et al., 2015). Therefore, more research is still needed, based on new machine learning methods and using improved technologies.

Future opportunities could lie in the development of complete real time systems to monitor animal behaviours according to their natural biology and taking account of changes in environmental parameters to allow detection of behavioural alterations. The application of a system to detect mounting behaviours can be tested in different farm situations with different group sizes of pigs to improve the developed algorithm. In particular, monitoring that can accommodate the changing features of pigs during the whole period of husbandry (i.e. between birth and slaughter), with automatic adjustment of algorithms as animals grow or change reproductive status, is another area of research that affects the potential of machine vision outputs and needs to be addressed in future studies.

Future opportunities could lie in further technological development. The major practical challenges in automation of individual pig monitoring due to various indoor and outdoor farm environments, in combination with the fact that the animals in a group can be highly similar in shape, colour and size, might be addressed by research based on new machine learning methods and using 3D features of animal body shape. There is also a need for the development of intelligent systems to monitor animal behaviours according to their natural biology and the pertaining environmental parameters, allowing for detection of behavioural alterations indicative of early health or welfare problems. Most of the studies on pig monitoring are based on complex programming algorithms and the system operability, particularly how easy and friendly usage is for farmers, is another dimension that can be improved in future. Nowadays, thanks to wide accessibility of networks and smart phone devices on farms, much more research effort needs to be carried out toward availability of real-time online monitoring with alarm systems on these devices to address the problem of commercial accessibility.

Pig monitoring is accompanied by recording large amounts of video data during animal husbandry; compiling and analysing these data is a challenge facing most researchers when evaluating their findings and results. Standard databases or automated data cleaning and selection could be utilized for large scale evaluation and monitoring systems to reduce costs and timing demands.

Table 1-A (appendix A) and Table 2-A summarise the automatic 2D and 3D image processing methods used for the different characterisation parameters and behavioural categories in cattle and pigs which have been reviewed in the thesis. These show that both 2D and 3D machine vision systems have been most commonly applied as a cheap and non-invasive ways to detect behaviour, individual and group features in cattle and pigs. Only in some cases have researchers developed and tested the systems in commercial conditions, which is one of the main goals in livestock automation research. Thus, in future, greater effort should be focused on more effective practical application of both 2D and 3D machine vision approaches to monitoring of individual and group livestock (e.g. automatic individual tracking, injurious interactions between pen mates) which are still challenging. In order to improve the efficiency, labour and energy cost of keeping large numbers of animals in commercial applications, collaboration is needed among animal building designers, to make the farm environment more suitable for automatic monitoring, animal biologists, to define animal requirements and interpret responses, and control, process modelling and machine vision specialists to refine available tools.

8. Summary

Real-time monitoring of animal health, welfare and behaviour is the key factor for farmers to manage the farm and achieve the highest income. Employing modern monitoring technology has helped farm managers to improve animal production and welfare and there are now many different types of machine vision techniques which could be used in new commercially-applicable technology tools. With accurate information about livestock behaviours, the farmer can move quickly to address problem pens or seek interventions. Additionally, automated monitoring of the time course and frequency of some abnormal behaviours within pens could facilitate the work of researchers exploring methods for prevention or alleviation of the behavioural problem. Due to the importance of monitoring animal behaviours in commercial production, a series of research studies was carried out in a commercial pig farm in Stafford, UK, for automatic detection of group lying behaviours in different environmental conditions, along with mounting events among pigs. Figure 8.1 shows the overall scheme of the developed monitoring system. In this research the image processing algorithms were developed using MATLAB® software.

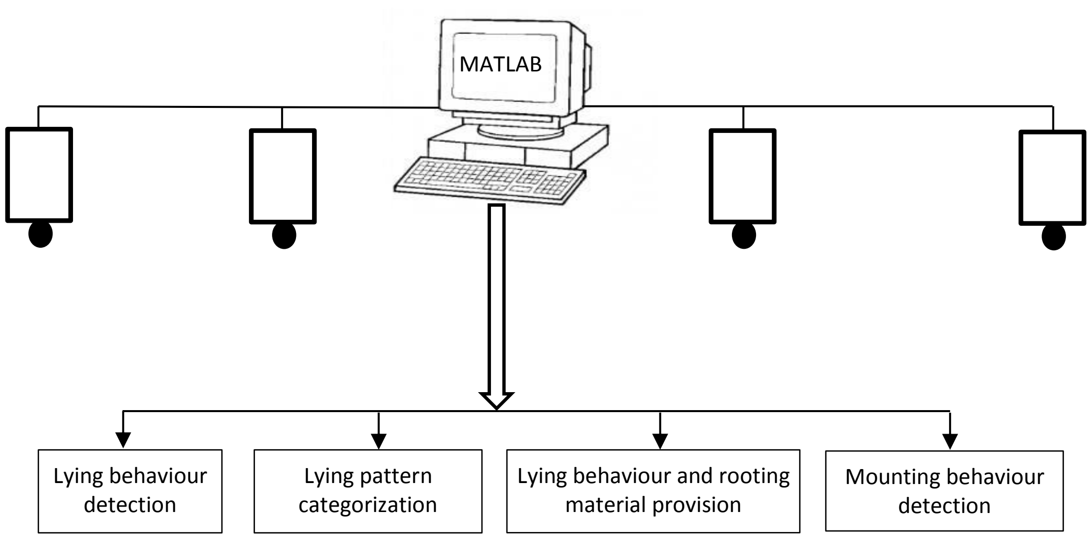


Figure 8.1- General scheme of monitoring system used in this research.

Pig lying patterns can provide information on environmental factors affecting production efficiency, health and welfare. One objective of this study was to investigate the feasibility of using image processing and the Delaunay Triangulation (DT) method to detect change in group lying behaviour of pigs under commercial farm conditions and relate this to changing environmental temperature. Two pens of 22 growing pigs were monitored during 15 days using top view CCD cameras.

Animals were extracted from their background using image processing algorithms, and the *x*–*y* coordinates of each binary image were used for ellipse fitting algorithms to localize each pig. By means of the region properties and perimeter of each DT, it was possible to automatically find the changes in lying posture and location within the pen of grouped pigs caused by temperature changes. Over a 15 day period, 39898 frames were analysed for the lying behaviour detection study and the results showed that the image processing technique yielded an acceptable level of correct detection (around 96 %). The developed method could contribute in the future as an important and economically feasible technique in commercial farms for assessment of livestock welfare in terms of the adequacy of environmental conditions. This is an important step towards the development of an automated system that can detect over time exact lying patterns and location of pigs during lying time by image features.

A study for the definition and categorization of lying patterns of grouped pigs in different ambient temperatures was conducted in four pens with 22 pigs. Three thermal categories were defined relative to room set-point temperature (21^{o}C), i.e. ARST (around the room set temperature, from 19 to 23^{o}C), LRST (lower than the room set temperature, from 14 to 18^{o}C), and HRST (higher than the room set temperature, from 24 to 28^{o}C). An image processing technique based on the DT was utilized. Different lying patterns (close, normal and far) were defined based on the perimeter of each DT triangle, and the percentages of each lying pattern were obtained for each thermal category. A method using a Multilayer Perceptron (MLP) neural network to automatically classify group pig lying behaviours into the three thermal categories was developed and tested for its feasibility. The DT features (mean value of perimeters, maximum and minimum length of sides of triangles) were calculated as inputs for the MLP classifier. The network was trained, validated and tested and the results revealed that MLP could classify lying features with a high overall sensitivity, specificity and accuracy (varying from 93.0% to 97.4%) into the three thermal categories. The technique indicates that a combination of image processing, MLP classification and mathematical modelling can be used as a precise method for quantifying pig lying behaviour in welfare investigations.

The application of the method developed to monitor pig lying behaviour was demonstrated in a study on the effects of environmental enrichment on pig behaviour. To deliver good animal welfare, pigs should have a hygienic and undisturbed lying area within the pen. So, a study was carried out to determine whether daily provision of a rooting material (maize silage) onto a solid plate in the lying area of a fully slatted pen resulted in changed lying location. The lying patterns of 6 groups of pigs in enriched pens were compared with those of control pens which had only a suspended enrichment toy. Since visual monitoring of pig behaviours over long periods is very time consuming, the developed image processing technique was applied to identify changes in pig lying positions and behaviour. Each pen was virtually subdivided into four zones and the position of each lying pig obtained at 10 minute intervals over a series of 24 periods. Results indicated that once daily provision of rooting material significantly changed the diurnal activity pattern ($p<0.001$) and resulted in a modified diurnal pattern of resting location. The results demonstrate that the developed machine vision approach can be used as a precise and fast method for quantifying pig lying behaviour for research or practical applications.

Since excessive mounting behaviours amongst pigs cause a high risk of poor welfare, arising from skin lesions, lameness and stress, and economic losses from reduced performance, a further objective of this research was to develop a method for automatic detection of mounting events amongst pigs under commercial farm conditions by means of image processing. Two pens were selected for the study and were monitored for 20 days by means of top view camera. The recorded video was then visually analysed for selecting mounting behaviours, and extracted images from the video files were subsequently used for image processing. An ellipse fitting technique was applied to localize pigs in the image. The intersection points between the major and minor axis of each fitted ellipse and the ellipse shape were used for defining the head, tail and sides of each pig. The Euclidean distance (Ed) between head and tail, head and sides, the major and minor axis length of the fitted ellipse during the mounting were utilized for development of an algorithm to automatically identify a mounting event. The proposed method could detect mounting events with high level of sensitivity, specificity and accuracy, 94.5, 88.6 and 92.7%, respectively. The results show that it is possible to use machine vision techniques in order to automatically detect mounting behaviours among pigs under commercial farm conditions.

In summary, the machine vision approaches developed and tested in this research programme were effective in automatically monitoring different behaviours of group-housed pigs under commercial farm conditions. Although many machine vision techniques have been developed and applied for livestock behaviour detection, further elaboration of image processing techniques could be an important step towards the development of an automated system that can detect behavioural changes of animals and decide and implement appropriate solutions, or generate alarms in unusual situations.

9. Zusammenfassung

Für die erfolgreiche Unternehmensführung landwirtschaftlicher Betriebe und zu deren Einkommenssteigerung ist die Echtzeitüberwachung von Tiergesundheit, -wohl und –verhalten ein Schlüsselfaktor. Der Einsatz moderner Tierüberwachungstechnologien ermöglicht es den Landwirten eine hohe Tierproduktion mit einem hohen Tierwohl im Einklang zu bringen. Neuartige Verfahren der Bilderkennung haben ein hohes Potential durch eine noch präzisere Tierüberwachung für weitere Steigerungen von Tierwohl und Ertrag zu ermöglichen. Präzisere Daten zum Tierverhalten erlauben es dem Betriebsleiter, schneller auf potentielle Probleme zu reagieren und Gegenmaßnahmen einzuleiten. Weiterhin kann die automatische Bilderkennung durch die Erfassung der zeitlichen Abfolge und Häufigkeit von auffälligen Verhaltensmustern die Arbeit von Wissenschaftlern bei der Forschung zur Verminderungs- und Präventionsstrategien zur Vermeidung von Verhaltensstörungen und tiergesundheitlichen Problemen unterstützen. Aufgrund dieses Potentials der Bilderkennung für die praktischen Betriebe wurde eine Serie wissenschaftlicher Untersuchungen auf einem Schweinemastbetrieb in Stafford, Großbritannien, mit Fokus auf die automatische Erfassung des Gruppenliegeverhaltens in unterschiedlichen Stallklimabedingungen und der Erkennung des Aufreitverhaltens durchgeführt. Abbildung 9.1 gibt eine Übersicht über das in diesem Kontext entwickelte System. Alle in diesen Forschungsarbeiten entwickelten Bilderkennungsalgorithmen wurden unter der Nutzung von MATLAB® entwickelt.

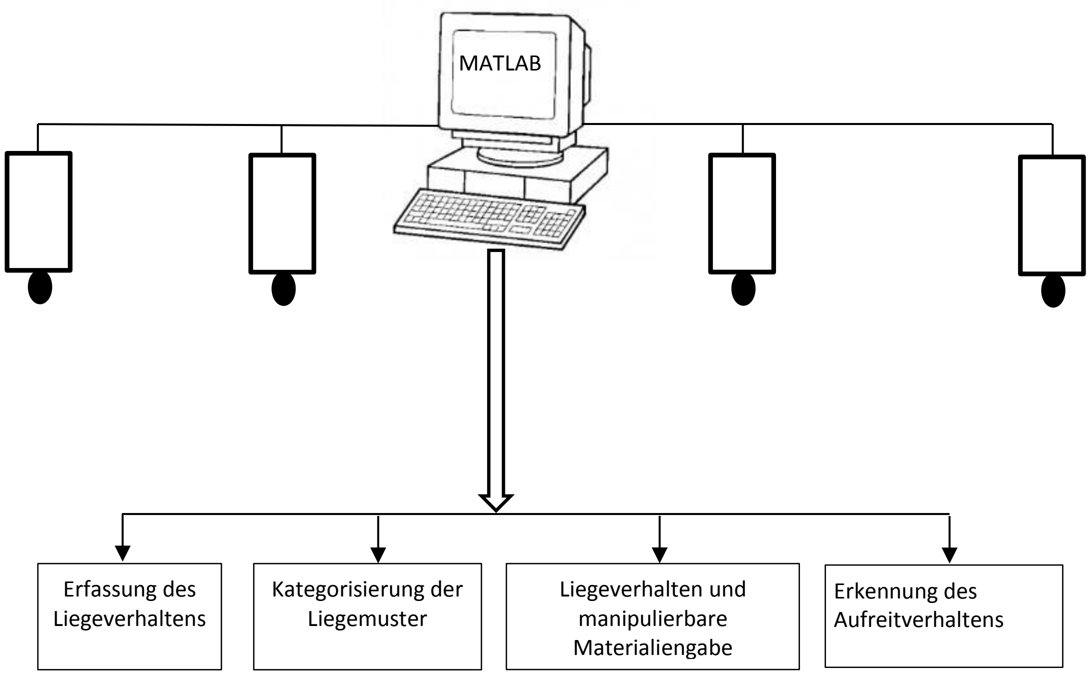


Abbildung 9.1 - Schema des in dieser Arbeit verwendeten Überwachungssystems.

Das Liegeverhalten von Schweinen kann als Indikator wichtige Informationen darüber liefern wie Umgebungsbedingungen (Raumtemperatur, Stallluft, etc.) die Produktionseffizienz, die Tiergesundheit und das Tierwohl beeinflussen. Eine zentrale Zielsetzung dieser Dissertation war die Untersuchung der praxisrelevanten Umsetzbarkeit von Bilderkennungsmethoden unter der Nutzung von Delaunay Triangulation (DT) zur Evaluierung des Liegeverhaltens von in Buchten gehaltenen Schweinen, insbesondere in Abhängigkeit der Umgebungstemperatur. Zwei Buchten mit jeweils 22 Mastschweinen wurden über einen Zeitraum von 15 Tagen mit CCD-Kameras überwacht, welche an der Stalldecke montiert eine komplette Übersicht über die jeweilige Einzelbucht ermöglichten. Die Tierkonturen in den einzelnen Bildern wurden unter Nutzung eines selbst entwickelten Bildauswertungsalgorithmus vom Hintergrund (Stallboden) separiert, in ein Binärbild umgewandelt. Anschließend wurden die x- und y-Koordinaten der genauen Position der Tierkonturen der einzelnen Schweine in jedem Einzelbild mittels Ellipsenanpassungssalgorithmen bestimmt. Die temperaturveränderungsbedingte Anpassung der Liegeanordnung und Positionierung der Gruppe wurde durch Einsatz der Koordinaten und des Umfangs jeder DT, erfolgreich ermittelt. Insgesamt wurden in den 15 Versuchstagen 39.898 Bilder erzeugt und ausgewertet. Die Ergebnisse zeigen, dass das entwickelte Bildverarbeitungsverfahren ein hohes Korrektheitsmaß im Vergleich zur manuellen Auswertung von 96 % aufweist. Die entwickelte Bilderkennungsmethode ist somit geeignet das Liegeverhalten der Schweine zu erfassen und kann zur Beurteilung der

Umgebungsbedingungen und deren Auswirkungen auf das Gruppenwohl in kommerziellen Schweinemastbetrieben eingesetzt werden. Aufgrund der geringen technischen Anforderungen an die Mess- und Auswertungshardware kann davon ausgegangen werden, dass die entwickelte Methode in der Praxis wirtschaftlich einsetzbar ist. Dies ist ein wichtiger Schritt hin zu der Entwicklung eines marktfähigen automatisierten Bildererkennungssystems welches exakt die Position von Schweinen und die entstehenden Liegemuster in der Gruppe erfassen kann.

Die zweite Studie zur Bestimmung und Charakterisierung der Liegemuster von in Gruppen gehaltenen Schweinen bei unterschiedlichen Umgebungstemperaturen wurde in insgesamt 4 Buchten mit jeweils 22 Schweinen durchgeführt. Es wurden drei thermische Kategorien in Bezug auf die Solltemperatur des Stalles (21°C) definiert: ARST (um die Solltemperatur, 19-23°C); LRST (niedriger als die Solltemperatur, 14-18°C) und HRST (höher als die Solltemperatur, 24-28°C). Basierend auf dem Umfang jedes DT Dreiecks wurden drei Liegemuster (eng, normal und weit) der Schweinegruppen definiert und die prozentuale Verteilung jedes Musters für jede thermische Kategorie bestimmt. Zur Klassifizierung der Liegemuster in die drei Temperaturkategorien wurde ein neuronales Netzwerk mit mehrlagigen Perzeptron (MLP) entwickelt. Die DT Merkmale (Durchschnittswert des Umfangs, maximale und minimale Länge der Seiten des DT) wurden als Eingangsgrößen für die MLP Klassifizierung berechnet und das Netzwerk wurde damit trainiert, validiert und getestet. Die Ergebnisse zeigen, dass das MLP das gezeigte Liegeverhalten mit einer hohen Gesamtsensitivität, Spezifität und Genauigkeit (93% bis 97.4%) in die drei thermischen Kategorien klassifizieren kann. Es konnte somit der Beweis erbracht werden, dass das entwickelte Verfahren bestehend aus einer Kombination von Bilderkennung und mathematischer Modellierung mittels MLP Klassifizierung als präzise Methode zur Quantifizierung des Liegeverhaltens von Schweinen in Bezug auf das Wohlbefinden der Tiergruppe geeignet ist.

In einer dritten Studie wurde die entwickelte Methode am Beispiel einer Untersuchung zur Auswirkung der Gabe von Wühlmaterialien auf das Liegeverhalten von Schweinegruppen untersucht. Für ein hohes Tierwohl, sollten Schweine Zugang zu einer hygienisch einwandfreien und ungestörten Liegezone haben. Daher wurde in einer weiteren Studie untersucht, inwieweit sich die tägliche Gabe von Wühlmaterial (Maissilo) auf einem planbefestigten Stallboden in der Liegezone auf das Liegeverhalten auswirkt. Die Liegemuster von sechs Gruppen von Schweinen, welche Wühlmaterial erhalten hatten, wurden mit dem Liegeverhalten von Schweinen in Kontrollbuchten, welche lediglich über hängendes Beschäftigungsmaterial verfügten, verglichen. Da die visuellen Beobachtungen des Verhaltens der Schweine sehr zeitaufwendig ist, wurde das entwickelte Bildverarbeitungsverfahren zur

Bestimmung eventueller Veränderungen im Liegeverhalten angewandt. Jede Bucht wurde virtuell in 4 Zonen unterteilt und die Veränderung der Position der liegenden Schweine in 10 Minuten Intervallen während der Aktivitätsphase des Tages (24 Intervalle / Tag) aufgenommen. Die Ergebnisse zeigen, dass eine einmalige Gabe des Wühlmaterial während der Tagesstunden die Aktivitätsmuster ($p<0,0001$) beeinflusst und in einer Veränderung des täglichen Aktivitätsmuster innerhalb des Liegebereiches resultiert. Es konnte somit demonstriert werden, dass das entwickelte Bilderkennungsverfahren zur schnellen und präzisen Quantifizierung des Liegeverhaltens bei Schweinen sowohl in der Wissenschaft als auch der Praxis eingesetzt werden kann.

Das Auftreten exzessiven Aufreitens stellt eine signifikante Minderung des Tierwohls in der Schweinehaltung dar. Ursachen hierfür sind die durch das Aufreiten hervorgerufenen Verletzungen wie Hautläsionen und Lahmheiten und der hervorgerufene Stress in der Schweinegruppe, welche wiederum zu einer Reduktion der Tierleistung führen können. Daher war ein weiteres Ziel dieser Dissertation, eine auf Bildverarbeitung basierende Methode zu entwickeln, welche es ermöglicht das Aufreitverhalten in einer Tiergruppe unter Praxisbedingungen zu überwachen. Für diese Studie wurden zwei Buchten für 20 Tage mittels Kameras mit Übersichtsperspektive überwacht. Die aufgenommenen Videos wurden manuell bonitiert um die Zeitpunkte des Aufreitens zu erfassen. Die betreffenden Bilder wurden aus den Aufnahmen extrahiert und für die Bildverarbeitung verwendet. Zur Lokalisierung der einzelnen Tiere wurde eine Ellipsenanpassungsmethode anhand der Konturen der im Kamerabild erfassten Schweine verwendet (s.o.). Die Kreuzungspunkte zwischen der Haupt- und Nebenachse jeder Ellipse sowie deren Form wurden zur Bestimmung des Kopfes, des Schwanzes sowie der Seiten der Einzeltiere verwendet. Die Euklidische Distanz (Ed) zwischen Kopf und Schwanz, Kopf und Seite, sowie die Haupt- und Nebenachsenlängen der angepassten Ellipse während des Aufreitereignisses wurden zur Entwicklung eines Algorithmus zur automatischen Erkennung von Aufreitereignisses genutzt. Die vorgestellte Methode war dazu in der Lage, Aufreitereignisse mit einem großen Maß an Sensitivität, Spezifität und Genauigkeit zu bestimmen (94,5%, 88,6% und 92,7%). Wiederum zeigten die Ergebnisse klar, dass es möglich ist unter Nutzung von Bilderkennungstechniken, das Aufreitverhalten in kommerziellen Ställen zuverlässig zu erfassen.

Zusammenfassend kann gesagt werden, dass der in dieser Arbeit entwickelte Ansatz der Integration von Methoden der Bilderkennung eine effektive Einbindung in eine automatisierten Überwachung unterschiedlicher Verhaltensmerkmale von in Gruppen gehaltenen Schweinen in Praxisställen erlaubt. Obwohl bereits eine Reihe von Bilderkennungsmethoden zur Erfassung von Tierverhalten existieren und Verwendung finden, konnte gezeigt werden das durch die Anwendung innovativer Auswertungsverfahren (DT und MLP) weiterhin ein großes Potential der Bilderkennung zur Entwicklung automatisierter Bilderkennungssysteme zur Erfassung und Auswertung von Verhaltensänderungen in der Schweinehaltung vorhanden ist. Insbesondere in der Entwicklung von Managementempfehlungen anhand des erfassten Tierverhaltens liegt noch ein großer Aufgabenbereich.

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Appendix A

Table 1-A Summary of automatic 2D and 3D image processing methods used for cattle monitoring.

Monitoring	Imaging system	Technique	Source
Live weight	2D (CCD camera)	Based on hip height, body length, hip width and chest depth.	Tasdemir et al., 2011a; 2011b; Ozkaya, 2013
	2D (Thermal camera)	Based on tail root and front hoof templates.	Stajnko et al., 2008
	3D (TOF sensor)	Based on 3D and contour features of body.	Anglart, 2016
Body shape and condition	2D (CCD camera)	Based on anatomical points (points around hook and tail).	Bewley et al., 2008; Azzaro et al., 2011
	2D (CCD camera)	Based on the angles and distances between anatomical points and the ED from each point in the normalized tail-head contour to the shape centre.	Bercovich et al., 2013
	2D (CCD camera)	Based on RGB and body features.	González-Velasco et al., 2011; Hertem et al., 2013
	2D (Thermal camera)	Based on thickness of fat and muscle layers.	Halachmi et al., 2008; Halachmi et al., 2013
	3D (TOF and depth imaging sensors)	Based on body features and back postures.	Weber et al., 2014; Salau et al., 2014; Fischer et al., 2015; Kuzuhara et al., 2015; Spoliansky et al., 2016
Health and disease	2D (Thermal camera)	Based on udder surface temperature.	Schaefer et al., 2004; Montanholi et al., 2008; Hovinen et al., 2008; Colak et al., 2008; Rainwater-Lovett et al., 2009; Wirthgen et al., 2011; Gloster et al., 2011; Hoffmann et al., 2013
	2D (Thermal camera)	Based on body surface temperature.	Cortivo et al., 2016
Feeding and drinking behaviour	2D (Thermal camera)	Based on the Viola–Jones algorithm.	Porto et al., 2012; Porto et al., 2015
	3D (Structured light illumination scanning)	Based on change in volume of food.	Shelley, 2013

Table 1-A (continued)

Monitoring	Imaging system	Technique	Source
Lying behaviour	2D (CCD camera)	Based on the x–y coordinates of the geometric centre of the animal.	Cangar et al., 2008
		Based on Viola and Jones algorithm.	Porto et al., 2013
Locomotion and lameness behaviour	2D (CCD camera)	Based on body features extraction from binary image.	Song et al., 2008
		Based on the touch and release angles in the fetlock joint of leg along with pressure mat data.	Pluk et al., 2012
		Based on the curvature of the back of each animal.	Poursaberi et al., 2010; Viazzi et al., 2013
	3D (Kinect sensor)	Based on 3D and 2D features of depth and binary images.	Viazzi et al., 2014a
	3D (Depth video)	Based on tracking hooks and spine of animal in depth image.	Abdul Jabbar et al., 2017
Aggressive behaviour	2D (CCD camera)	Based on geometric features between animals.	Guzhva et al., 2016
Mounting behaviour	2D (CCD camera)	Based on motion detection and length of moving animals.	Tsai and Huang, 2014

Table 2-A Summary of Automatic 2D and 3D image processing methods used for pig monitoring.

Monitoring	Imaging system	Technique	Source
Live weight	2D (CCD camera)	Based on length and width dimension and boundary area.	Schofield, 1990; Brandl and Jorgensen, 1996; Schofield et al., 1999; Doeschl-Wilson et al., 2004
		Based on area, convex area, perimeter, eccentricity, major and minor axis length.	Wang et al., 2008; Kashiha et al., 2014b ; Wongsriworaphon et al., 2015;
	3D (Kinect sensor)	Based on volume and area of body.	Kongsro, 2014; Zhu et al., 2015
	3D (Stereo Vision)	Based on body length, withers height and back area.	Shi et al., 2016
Body shape and condition	2D (Thermal camera)	Based on shape and contour detection.	Liu and Zhu, 2013
	3D (Stereo photogrammetry)	Based on triangulating on animal natural skin texture.	Wu et al., 2004
Health and disease	2D (CCD camera)	Based on daily movement pattern in binary images.	Zhu et al., 2009
Tracking	2D (CCD camera)	Based on blob edge and an ellipse fitting technique.	McFarlane and Schofield, 1995; Kashiha et al., 2013b
		Based on x-y coordinates of shape.	Tillett et al., 1997
		Based on positions of locatable features (kinks) of body.	Frost et al., 2000
		Based on RGB values.	Jover et al., 2009
		Based on building up support maps and Gaussian model.	Ahrendt et al., 2011
		Learning based segmentation	Nilsson et al., 2015

Table 2-A (continued)

Monitoring	Imaging system	Technique	Source
Tracking	2D (CCD camera)	Based on adaptive partitioning and multilevel thresholding segmentation.	Guo et al., 2015
Feeding and drinking behaviour	2D (CCD camera)	Based on fitted ellipse features and distance to drinking nipple.	Kashiha et al., 2013a
Lying behaviour	3D (Kinect sensor)	Based on depth image and x-y coordinates of binary image.	Lao et al., 2016
	2D (CCD camera)	Based on features of binary image.	Shao et al., 1998; Shao and Xin, 2008
		Based on the pixel intensity in binary image.	Costa et al., 2014
		Based on fitted ellipse and the DT features.	Nasirahmadi et al., 2015; 2016a ; 2017b
Locomotion and lameness behaviour	2D (CCD camera)	Based on RGB and image map values.	Kongsro, 2013
		Based on activity index.	Ott et al., 2014
		Based on fitted ellipse features in consecutive frames.	Kashiha et al., 2014a; Nasirahmadi et al., 2015
		Based on optical flow pattern.	Gronskyte et al., 2015; Gronskyte et al., 2016
	3D (Kinect sensor)	Based on Vicon 3D optoelectronic motion analysis.	Stavrakakis et al., 2015a; 2015b
Aggressive behaviour	2D (CCD camera)	Based on motion history image and activity index.	Viazzi et al., 2014b; Oczak et al., 2014
	3D (Kinect sensor)	Based on features from depth image.	Lee et al., 2016
Mounting behaviour	2D (CCD camera)	Based on fitted ellipse features and ED between animals.	Nasirahmadi et al., 2016b