Design and Implementation of an IoT Enabled Generic Platform for Precision Livestock Farming and Applications

Yukang Han

In the fulfilment of the requirement for the degree of

Master of Philosophy

Centre for Signal and Image Processing
Department of Electronic and Electrical Engineering
University of Strathclyde, Glasgow
United Kingdom

Supervised by

Doctor Jinchang Ren

Professor James Windmill

June 1, 2020

Declaration of Authorship

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Yukang Han

June 1, 2020

Acknowledgements

As time goes by, my career as a student is coming to an end. In this beautiful city of Glasgow, I can still remember the first impression when I stepped out of the Glasgow airport, where I just landed from the other side of the world with full of the excitement and expectation about my upcoming life and study at the University of Strathclyde.

First, I would like to express my deepest sense of gratitude for my supervisor Dr Jinchang Ren, who is a knowledgeable and gentle person for the guidance and support in my research career. He also encouraged me to participate in various roles and provided insightful thoughts and guided me through. His rigorous academic attitude and integrity will always remind me to pursue a better self, and his skilful guidance, innovative ideas and patience are greatly appreciated. I would also like to thank my second supervisor Prof. James Windmill for the help in my study. Thanks to my colleagues, it was a great pleasure working with you all, and I appreciate all the help and support.

Thanks to my parents, who support my studying in a foreign county and provide help as much as they can. A very special thanks to my wife, Xinyi, who offered tremendous support and understanding during my time. I am very lucky to have these wonderful people in my life, and I appreciate all the support.

I would also like to thank the KTP project for the opportunity of allowing me to participate with an industrial partner in the field of precision livestock farming. David Barclay and Qiming Zhu who offered vast help and trust during my time in Innovent Technology. The project went smoothly and successfully in delivering the R&D work, which have all contributed to building a solid relationship between the University of Strathclyde and the Industrial partner, Innovent Technology.

This study is partially funded by the Knowledge Transfer Partnership (KTP) project with Innovate UK and Innovent Technology in partnership with the Department of Electronic and Electrical Engineering, University of Strathclyde.

Abstract

This thesis focuses on precision agriculture of livestock farming. Precision Livestock Farming is a modern farming development that emphasises on deploying advanced information and communication technology in physical farms to optimise the contributions of individual animals. Relevant techniques such as the Internet of Things (IoT), machine learning and 5G communication are all needed for improving the level of automation, intelligence and efficiency towards smart farming. With the support of more powerful computing resources, we are capable of handling massive volumes of data, where highly automated processes can be applied for data capturing, analysis and improved decision making. In addition to the economic benefits, Precision Livestock Farming also meets several social goals, such as high-quality and safe food products, efficient and sustainable livestock farming, better animal welfare and low footprint to the environment.

Manual observation of animals is a tedious job, especially over a long time, and it can often be affected by the observer's bias. As a result, IoT enabled AI machine learning-based automatic monitoring and management of livestock with image processing and analysis can offer massive potential for producing the unbiased status report in a more efficient and effective way. By utilizing the real-time monitoring technology, and the corresponding management system can boost productivity whilst reducing the cost and environmental emissions in livestock farms.

To tackle this emerging issue and needs, a Precision Livestock Farming platform has been designed and implemented in this thesis, with the support of various sensors and corresponding analytics technologies. By continuously recording and analysing live data, it can not only recognise the welfare and health status of the animals but also for evidence-based smart decision-making with the support of the massive volumes of data. For implementing the proposed system, various techniques have been introduced to address the challenging issues, especially real-time multi-camera video streaming and transmission in an on-demand manner for improving the efficiency and efficacy in mobile/cloud-based environments.

As a case study, the developed generic platform has been applied for tracking and behaviour recognition of pigs. These include background detection, object detection, object classification and target selection, followed by object tracking and behaviour recognition. The successful application has not only validated the efficacy of the proposed system but also demonstrated the flexibility and great potential of the proposed system in a wide range of application areas.

Finally, some future directions are also provided after the summary of the contribution points, which are expected to benefit the further development of the corresponding fields and the automation and intelligence of the livestock farming.

KEYWORDS: PRECISION LIVESTOCK FARMING; GENERIC PLATFORM; ANIMAL TRACKING; BEHAVIOUR RECOGNITION; DEPTH IMAGE.

Table of Contents

Declaration of Authorship....................i

Acknowledgements....................ii

Abstract....................iii

List of Figures....................viii

List of Tables....................ix

List of Abbreviations....................x

Chapter 1. Introduction....................1

1.1 Motivation....................1

1.2 Objectives....................1

1.3 Contributions....................3

1.4 Organisation of the thesis....................3

Chapter 2. Literature Review....................5

2.1 Background....................5

2.2 Summary of Different Sensors....................6

2.3 Big Data in Smart Farming....................13

2.4 Livestock Behaviour Monitoring and Recognition....................14

2.4.1 Initialisation....................16

2.4.2 Features and cues selection....................17

2.4.3 Tracking....................18

2.4.4 Pose estimation and behaviour recognition....................20

2.5 Video Streaming....................20

2.6 Precision Livestock Farming Applications....................21

2.7 Summary....................21

Chapter 3. Generic Precision Livestock Farming Platform....................22

3.1 Introduction....................22

3.2 Hardware....................22

3.3 Software Architecture and Implementation 24
3.3.1 Streaming 26
3.3.2 Decoding 28
3.3.3 Synchronising 29
3.3.4 Analysing 30
3.3.5 Summarising 30
3.3.6 Visualising 31
3.4 Summary 33
Chapter 4. Tracking and Behaviour Recognition of Pigs 34
4.1 Introduction 34
4.2 Background 34
4.3 Method 36
4.3.1 Background detection 36
4.3.2 Object detection 37
4.3.3 Object classification 38
4.3.4 Target selection 40
4.4 Tracking 41
4.5 Behaviour recognition 42
4.6 Results 43
4.7 Summary 44
Chapter 5. Conclusion and future work 45
5.1 Conclusion 45
5.2 Future work 46
References 48
Appendix A 61
Appendix B 63
Appendix C 65

List of Figures

Figure 1 Concept of the precision livestock farming system. 3
Figure 2 Systems for electronics animal identification (Data from [8][10]). 5
Figure 3 Top view RGB camera in a pig pen (Image from [6]). 6
Figure 4 Depth camera image of a pig (Image from [9]). 7
Figure 5 Number of coughs per hour – Pig Cough Monitor (Image from [11]). 8
Figure 6 Cow carrying the collar with the geolocation device (Image From [14]). 10
Figure 7 Sheep with an ear tag (Image From https://en.wikipedia.org/wiki/Ear_tag). 11
Figure 8 Pig with painted numbers. 12
Figure 9 Pigs used for facial recognition (Image from [22]). 12
Figure 10 Animal behaviour cycle. 15
Figure 11 Recognition process. 16
Figure 12 Platform design. 21
Figure 13 Workflow of the software. 25
Figure 14 RTSP protocol workflow. 27
Figure 15 Bit rate comparison. (Image from [112]). 29
Figure 16 HTTP Polling and WebSocket throughput comparison (Image from [116]). 32
Figure 17 HTTP Polling and WebSocket latency comparison (Image from [116]). 33
Figure 18 Depth image captured in a pig pen. 35
Figure 19 Background detection. 37
Figure 20 Object detection. 38
Figure 21 Target selection. 40
Figure 22 Alpha-beta filter. 41
Figure 23 Source Image. 43
Figure 24 Reference Image. 43
Figure 25 Result Image. 43

List of Tables

Table 1 Push and pull factors for Smart Farming (Data from [1]). 13

Table 2 Behaviour recognition process. 16

Table 3 Feature extraction techniques. 19

Table 4 Ingress Protection ratings (data from [131]). 23

Table 5 Comparison of push and pull protocols. 26

Table 6 HTTP polling performance test (Data from [116]). 32

Table 7 WebSocket performance test (Data from [116]). 32

Table 8 Filter parameters for pigs. 40

Table 9 Recognition Comparison. 43

Table 10 Summary image processing methods used for cattle monitoring. 61

Table 11 Summary image processing methods used for pig monitoring. 62

List of Abbreviations

2D	Two Dimensional
3D	Three Dimensional
LF	Low Frequency
PLF	Precision Livestock Farming
QR Code	Quick Response Code
RFID	Radio Frequency Identification
TOF	Time of Flight
UHF	Ultra High Frequency
IP camera	Internet Protocol camera
IP rating	Ingress Protection rating
TCP	Transmission Control Protocol
UDP	User Datagram Protocol
API	Application programming interface
FFmpeg	Fast Forward Motion Picture Experts Group
PRRS	Porcine Reproductive and Respiratory Syndrome
PEDv	Porcine epidemic diarrhoea
PCV2	Porcine circovirus associated disease type 2
ASF	African swine fever
ROI	Region of Interest
NaN	Not a Number

Chapter 1.

Introduction

Precision Livestock Farming is a modern farming development that emphasises on deploying advanced information and communication technologies in physical farms to reduce human involvement in the whole management process [1]. It refers to utilise real-time monitoring and management to boost the productivity of management and automation of the production process in livestock farms. Those devices can introduce more intelligence, reduce the number of labours, and provide evidence for smart decision-making. The availability of various sensors and analytics technologies have significantly changed the way of modern farming.

1.1 Motivation

Livestock production is one of the essential food sources in our daily life. It has a long history in the human diet and is able to provide rich protein and nutrition for our daily activities. Considering the increasing population worldwide and growing demands for high-quality meat and milk, this has posed a challenging question to the government and livestock enterprises as to how to produce enough food to feed the growing population. Such demand is expected to increase by 70% by 2050, which has called for expanded and efficient production [3][4].

Although the price of various sensors and computing devices has been dropping, the adaptation of these technologies varies widely in countries and regions as well as across different cultures. However, there are mainly three reasons for farmers and governments to rethink their current practices and embrace new changes, which are summarised below [5].

1) Economic benefits through reductions in farm expenditure via the controlled applications of agriculture inputs;
2) Increased yields from targeted management of in-field variability;
3) Environmental benefits by the precise use of agrochemical applications, which increases compliance with national environmental legislation.

1.2 Objectives

Although many works have been done for precision livestock farming, their efficiency, efficacy and working environment vary significantly in different areas, countries and regions. The main challenging problem is the lack of a standardised generic platform that can integrate up-to-date technologies with different farming devices for continuously monitoring and management of the animals. These can then be used for routinely capturing real-time images for analysing of interested events, detecting abnormal behaviours, and providing instant information to stakeholders for smart decision making.

The major objectives of this study can be summarised as follows:

- To investigate various sensor applications in the field of livestock farming and propose a generic platform for Precision Livestock Farming.
- To find ways to improve the design and implement the generic platform so that it can be running on different operating systems, and capable of expanding the capability by integrating IoT devices.
- To implement the streaming and decoding protocols as well as web-based visualisation technology for both RGB cameras and time-of-flight (ToF) cameras.
- To test the generic platform in real applications such as pigs for image-based automatic object recognition and tracking, behaviour analysis and recognition.

For the generic Precision Livestock Farming Platform, communication with different types of sensors is crucial. The software needs to be able to connect to cameras and other sensors installed in the farm, especially for continuously monitoring of the animals. Ideally, this software and the connected sensors need to be running on a 24x7 mode. On the one hand, it can thus provide sufficient data for next-step data processing. On the other hand, the data collected in a consistent and concentrated manner can be used to build a time-based model of events. With rich and more accurate data, we can track down to where and when the event happens and why, where a holistic model of the target animal will be formed with the accumulating dataset. For the animal growth model, we need to capture not only the image frames inside the farm but also other environmental data such as humidity, precipitation, illumination, CO_2 concentration and temperature of the environment. With all these animal associated data, we can achieve more effective analysing of the behaviour and making reasonable interventions. The figure below shows the concept of the proposed Precision Livestock Farming platform.

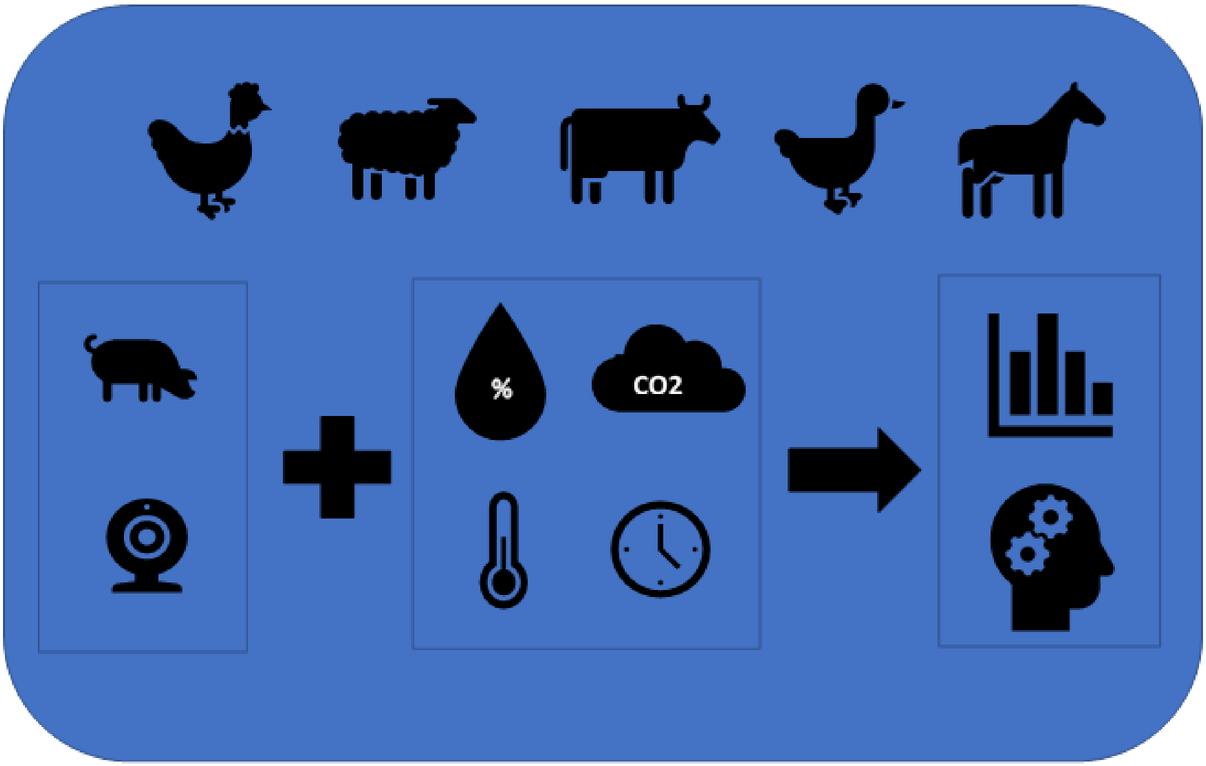

Figure 1 Concept of the precision livestock farming system.

1.3 Contributions

The major contributions of this thesis can be summarised as follows:

- A generic platform is proposed for Precision Livestock Farming.
- Comparison of steaming protocols and decoding methods for real-time image processing.
- Added fusion module into the architecture for integration of external data source.
- WebSocket technology for image visualisation, where a cross-platform visualisation solution for displaying real-time images.
- Streaming data from TOF cameras and processing the depth images.
- Animal tracking and behaviour recognition, especially to apply image processing and machine learning algorithms for detection and tracking of objects, where the motion features are then used for behaviour recognition for animal welfare.

1.4 Organisation of the thesis

This thesis includes five chapters. The first chapter introduces the background and motivation of the work, as well as the major aims and objectives. The second chapter covers the literature review, including related work in precision livestock farming, the technologies behind, Big

Data in agriculture as well as animal behaviour analysis, and corresponding applications. Chapter 3 presents the design and implementation of the proposed generic platform in two main aspects, i.e. the hardware system and the software, where several technical challenges are addressed in detail. Chapter 4 introduces a case study of the proposed generic platform in precision livestock farming of pigs. Finally, Chapter 5 concludes the thesis, along with a summary of some future directions.

Chapter 2.

Literature Review

2.1 Background

The concept of Precision livestock farming (PLF) is rather new. However, some early adopters are starting to take advantages of related technologies, such as automatic feeder, weight detection and climate control systems. However, the most intelligent part of PLF is constantly evolving, in which significant progress has been made in recent years [8]. In this chapter, related work will be analysed and discussed in detail.

One important development is the animal identification, which could enable personalised animal management and treatment on a large scale. Providing tailored care to animals could optimise the contribution of individual animals and set up a sustainable farming environment. Regardless of the scales or species, productivity and welfare of the animals would both be improved. The key to unlocking the potential of PLF is to enhance the traceability on each animal and share such data in the supply chain [8]. Figure 2 below shows related animal identification technologies used so far.

Operating principle	Information carrier	Process	Applications	Advantages	Disadvantages
Optical	Shape	Touching	Processing, fingerprinting	Biological characteristics	Contact required
	Shape and colour	Image processing	Processing, iris recognition, animal identification	Universal	Complex
	Number code	Code recognition	Automatic identification	Inexpensive	Complicated, dirties easily
	Barcode	Scanner	Trade goods, barcode on new ear markers	Extremely inexpensive markers	Dirties easily
	Electronics with infrared transfer (active)	Transceiver	Service of electrical equipment, animal identification	Large reading range, easily protectable	Only active systems are possible
Electromechanical	Surface acoustic waves (passive)	Transceiver	Goods identification, animal identification	Inexpensive sensor elements, quickly	Only for short information
Electronic	Transponder (active and passive)	Transceiver	Processing, logistics, vehicle security, animal identification	Universally applicable	Relatively expensive

Figure 2 Systems for electronics animal identification (Data from [8][10]).

2.2 Summary of Different Sensors

In order to better understand how various sensors and technologies are applied in the field of PLF, the following subsections will introduce different sensor technologies such as cameras, microphones, thermometers and radio frequency identification etc. and the functionalities of these sensors.

- **Cameras**

Cameras with the RGB, Depth and thermal sensors can capture data such as colour, depth, and infrared information from the environment. The captured data are usually sent directly to a processing unit where the data can be processed by software algorithms. An algorithm consists of a series of operations, typically aiming to solve a given task. In farming practices, the value of the algorithms usually subjects to its ability to transform the raw data into semantic or understandable biological characteristics while presents the outcome in a human-readable fashion. Examples of biological characteristics herein include the weight of animals, warfare status such as lameness, and aggressive behaviours such as tail biting. Taking all these into consideration, data captured from sensors can be combined with the identification of individual animals, referenced observations and the production data, and these can be further integrated into associated algorithms for providing credible information and alerting the animal welfare, health and productivity of the farm [1][2].

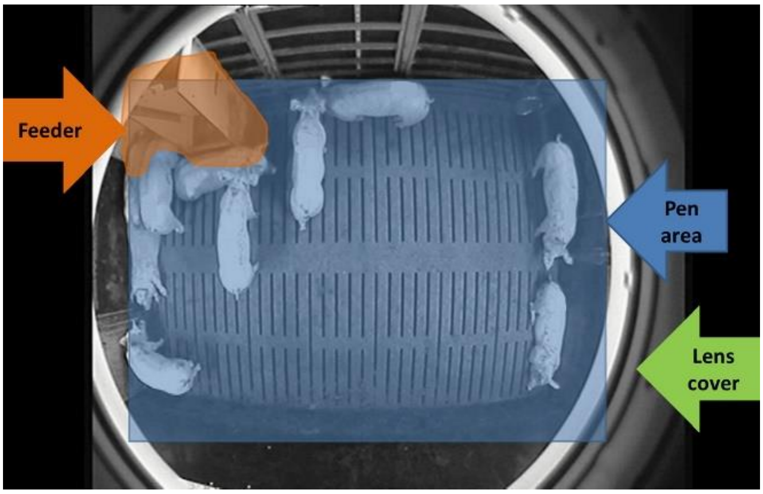

Figure 3 Top view RGB camera in a pig pen (Image from [6]).

The research developed in [6] demonstrated the use of a top view RGB camera in a pig pen to determine the locomotion of pigs in a group with high accuracy. Since locomotion is known to be associated with issues such as lameness, this result can give an accurate indication of the health and welfare conditions.

However, the RGB camera sensor often requires adequate ambient lighting in the environment with a contrasting background for differentiating the targeted objects from the background and the floor. Therefore, it is not a robust or reliable solution for a long-time continuous run. With the increasing advances in computing and availability of inexpensive 3D sensors developed for game industry (i.e. Xbox, PlayStation), 3D camera sensors can be combined with growing computing capacity for capturing and processing data in the field of PLF. Microsoft Kinect and RealSense from Intel are both 3D cameras capable of producing RGB, infrared and depth images. The infrared image is quite important for tasks like observing nocturnal behaviours, or data capturing with insufficient ambient lighting at the scene. In addition, the depth sensor is crucial to measure the distance from the objects to the camera.

Figure 4 shows as an example a depth image, where the pixels in red and blue within the image indicate the farthest and closest distance to the camera, respectively. The working principle behind the depth sensors is the Time-Of-Flight (TOF) technology, where the sensor frequently emits a light pulse which hits the external surface of the object and returns to the sensor. The time it takes to bounce back is then measured to provide depth-mapping of the scene. Also, the depth measurement can produce relatively accurate 3D Point-Cloud map of the scene where some advanced 3D geometry algorithms can be applied to the dataset such as 3D scanning, model creation and visualisation.

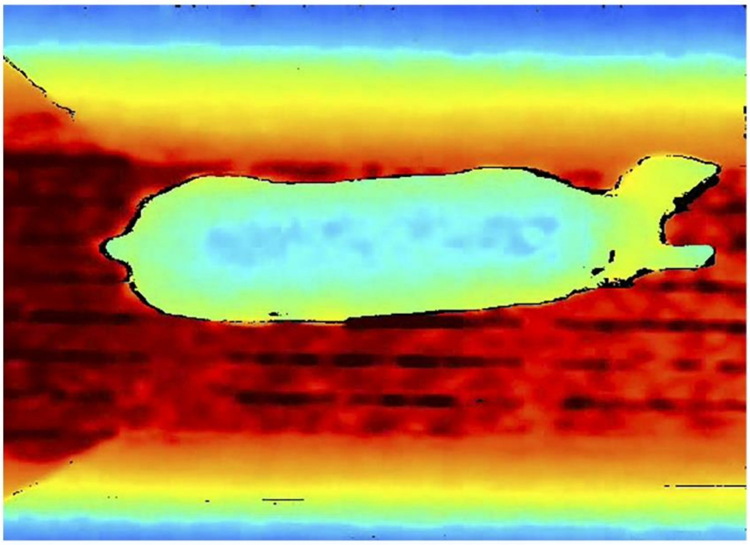

Figure 4 Depth camera image of a pig (Image from [9]).

- **Microphone**

Respiratory diseases are very common in animal farms, causing significant welfare problems and economic losses to farmers. Early intervention is crucial for reducing further deterioration and the number of antibiotics used in the process specifically for intensification livestock farming. Early warning allows in-time treatment. Hence it can lower the risk of spreading the diseases so as to reduce the time for the animals to recover [8].

Microphone sensors can capture sound waves in farms and convert it into electronic signals, and then, the signals can be analysed by specific signal processing algorithms with the intent of detecting certain diseases. Once the electronic signal deviates from its normal pattern, an alert will be sent to the responders. For example, coughing and squeezing can be reported to the respiratory warning system, and stressful or illness sound can be reported to the early intervention system [9]. In this way, farmers can be taking immediate actions before the detected changes and stop further deterioration among animals. These actions include solving technical problems such as blocked feeding lines, adjusting climate settings, or medical treatment to the animals, especially the preventive medicines to prevent the further spreading of respiratory diseases whilst mitigating the antibiotic resistance issue in the future [8].

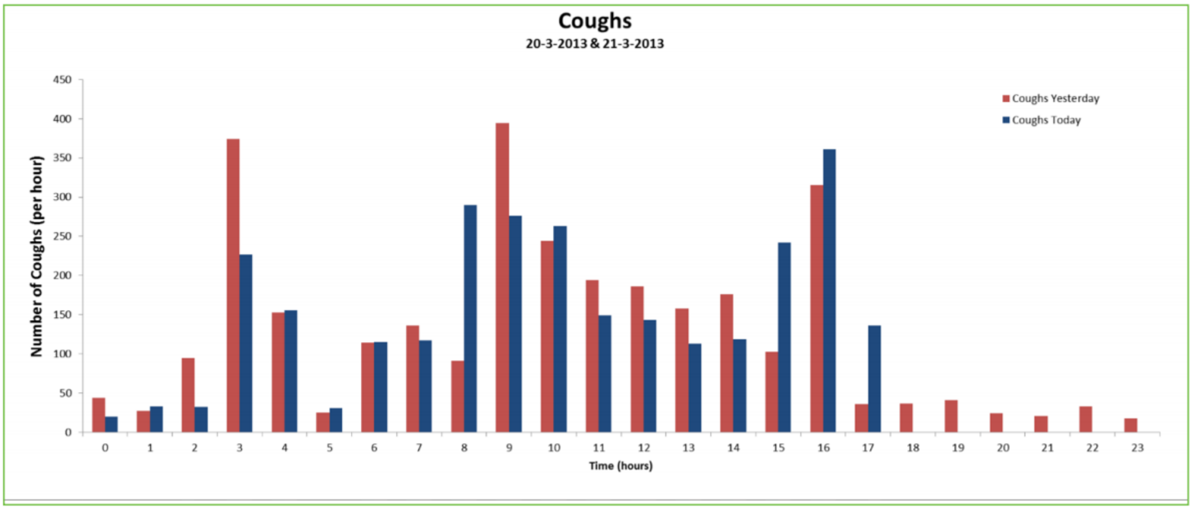

Figure 5 Number of coughs per hour – Pig Cough Monitor (Image from [11]).

Figure 5 illustrates a tool developed by the Funcom (Dutch) for continuously monitoring the occurrence of coughs in pigs. It consists of an analysing software and two microphones installed at different locations to record the sound. The sound is filtered initially to eliminate general pig sounds, which is then separated to identify coughs. The software allows farmers to configure the acceptable level of coughing against the pre-defined norms. When the sound exceeded the threshold, alarms would be raised with the information displayed in a diagram fashion. It can also be used as an early warning tool for tracking the aftereffect of the treatment [11].

The sound analysis is part of a larger system for PLF. It can provide more detailed information about the current threat and historical records, which can be compared with different farms and used to manage the risk of a widespread infection within the region.

- **Thermistor and Infrared Imaging**

Temperature is among one of the most classically measured parameters, which is also mostly related to various functions of the organism, such as nutrition, reproduction, activity, stress responses, and health. Usually, the temperature monitoring system uses a thermistor with an embedded data logger, where the thermistor has direct contact with the tissue of the subject in order to provide an accurate temperature reading to 0.1ºC [9][12]. Another approach is Infrared (IR) technology, which does not require physical contact with animals when measuring the temperature. That is because every object emits IR radiation when its temperature above the absolute zero (-273.15ºC), thus the wavelength of the IR radiation can be used to measure the temperature of the object. There are two types of infrared systems commercially available, IR thermometer and thermal camera, which are detailed below.

IR thermometer consists of a lens which focuses the infrared radiation onto the detector. It can convert thermal radiation into electronic signals, which can be displayed as a temperature unit. Spot infrared thermometer measures the temperature of a specific small spot area on the animal's body surface.

Infrared cameras are infrared radiation thermometers that measure the temperature at many points over a large area to generate a thermal image, in which each pixel represents the temperature unit of the spot. The generated image is called 'thermogram', which requires more software computing than spot infrared thermometer and usually used for monitoring large areas.

- **Accelerometer**

Wearable sensors are among one of the most rapidly developing electronic devices in recent years and contribute quite an amount deployment of new technologies for PLF. One popular application in outdoor cattle and sheep farming is the use of geolocation embedded electronic devices, usually carried by the animals, and wireless communication networks that transmit the collected position data to the users. The wireless communication protocols are based on existent wireless technologies such as GSM, Wi-Fi, or ZigBee. Figure 6 shows the geolocation device embedded into a collar carried by a cow [14].

Figure 6 Cow carrying the collar with the geolocation device (Image From [14]).

In [15], another wearable sensor application has been demonstrated by using a three-axis microelectromechanical system accelerometer to determine eating, ruminating and resting activities for cattle. The accelerometer fitted in cattle measures their under-jaw accelerations at an interval of one second. The raw acceleration data was processed to create twelve variables in total, including the mean, variance, and inverse coefficient of variation per minute for the x, y, and z axes. The results have shown that the total percentage of correct discriminations exceeds 90% in both tie-stalled and grazing cows.

- **Radio Frequency Identification (RFID)**

RFID is perhaps the most well-known technology in animal identification and management. The RFID system includes an RFID reader and an RFID tag. The reader is either embedded at a fixed position where the animals usually passed by or attached to a mobile device. There are three main types of tags used for the animals: boluses, ear tags, and injectable glass tags for being injected under the skin. Boluses are capsules, incorporating a radio frequency transponder, which is retained in one of the first two stomachs of the ruminants and it has been proven to be a safe choice for ruminant identification [16][17]. The injectable transponders, on the other hand, can be applied quickly after birth, while the preferable locations differ in each animal species [18].

Figure 7 Sheep with an ear tag (Image From https://en.wikipedia.org/wiki/Ear_tag).

In general, RFID tags can be classified into two categories: rewritable and non-rewritable [19]. For the non-rewritable tags, it only contains the tag's number, which can be associated with the animal wearing it. Rewriteable tags, on the other hand, can contain, apart from the ID, some additional information which can be used for the management of the animals. Information such as country ID and farm ID can be used for tracking the animals in a foreign environment. However, due to the very limited memory resource within the tag, it is always a good practice to choose what description information to be stored carefully.

Low frequency (LF) – RFID tags are commonly used in farms today for tracking and managing animals such as supplying specific food when the animal is detected in front of the feeder. However, it has two significant disadvantages. One is the low reading range, which usually is less than 1m. The other one is incapable of detecting more than one tag at the same time [20]. Ultra-high frequency (UHF) - RFID, on the other hand, can detect animals within 3-10m and simultaneous identifications of multiple tags. However, it still struggles with applying this technology due to the strong influence of the animal's tissue, leading to false detections and poor reading performance [20]. Other drawbacks of RFID include wear and tear in RFID, broken or eaten by other animals, pain and discomfort during installation and removal from the animals prior to transportation.

- **Optical Character Recognition**

This is the most classic and widely used identification technology in smart farming. Animals with printed symbols, stamps, or written text characters (license number, barcode, QR code et al.) on the body surface can be recognised by software algorithms. Large permutations of the symbols and colours can be identified by the algorithms without too much pain when marking the animals, and the identification marks may not need to be removed prior to transportation.

The disadvantage of this system is that the markings can be covered with dirt or wear and tear in a few days according to the living environment of the animal, especially for pigs, as shown in Figure 8, where the image contains a pig with a painted symbol on the body surface.

Figure 8 Pig with painted numbers.

- **Facial Recognition**

Facial recognition was originally developed for human identification, which uses biometrics to map facial features from a photo or video to find a match by comparing the information with a database of known faces. However, many research works have been investigating it for PLF, which is very much in line with the expectation of this technology. Examples of methods used for human face recognition are also applicable to pigs.

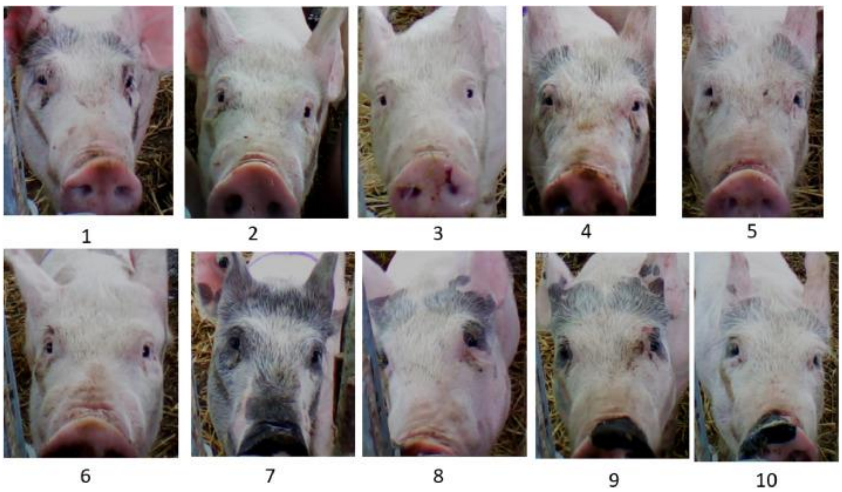

Figure 9 Pigs used for facial recognition (Image from [22]).

In [21], preliminary results have shown that the Eigenfaces technique could achieve a recognition performance of 77% on 10 pigs using the manually cropped faces. In [22], a camera is mounted behind a drinker station to take photos while pigs are nearby, these photos are used to develop software to identify the 10 pigs, see in Fig. 9, with an accuracy of 96.7%. The algorithms behind it can discriminate pigs mainly from three regions: the snout itself and the region above it that contain wrinkles, and the top of the head where the markings are most prevalent, and to a lesser extent, the eye regions.

2.3 Big Data in Smart Farming

Push factors	Pull factors
1) General technological developments - Internet of Things and data-driven technologies - Precision Agriculture - Rise of agri-tech companies **2) Sophisticated technology** - Global Navigation Satellite Systems - Satellite imaging - Advanced (remote) Sensing - Robots - Unmanned Aerial Vehicles (UAVs) **3) Data generation and storage** - Process, machine and human-generated - Interpretation of unstructured data - Advanced data analytics **4) Digital connectivity** - Increased availability to ag practitioners - Computational power increase **5) Innovation Possibilities** - Open farm management systems with specific apps - Remote/computer-aided advise and decisions - Regionally pooled data for scientific research and advice - Online farmer shops	**6) Business drivers** - Efficiency increase by lower cost price or market price - Improved management control and decision-making - Better local-specific management support - Better cope with legislation and paperwork - Deal with volatility in weather condition **7) Public drivers** - Food and nutrition security - Food safety - Sustainability **8) The general need for more and better information**

Table 1 Push and pull factors for Smart Farming (Data from [1]).

‘Smart farming’ is an initiative of using modern technologies to digitalise the traditional ways of farming activities by using information and communication based on intelligent analysis and automation. New technologies such as the Internet of Things (IoT), machine learning and 5G are employed to facilitate this development and introduce more intelligence in farming. Massive volumes of data generated during the production process will be used for analysing and providing valuable information.

Big data in the applications of livestock farming has begun to move out of the production territory and be integrated into the food supply chain. The advantages of providing evidence for operational decisions and real-time farming information to stakeholders have changed many business models [1]. This trend is mainly driven by push and pull factors. Pull, because of the farming industry has been long desired to increase its productivity. Push, because this new technology will raise the standards of the food industry as well as release tremendous manpower to boost other industries. Table 1 shows a summary of the relevant push and pull factors behind this change.

2.4 Livestock Behaviour Monitoring and Recognition

Animal behaviour is often reflected by its interactions with the environment, which can indicate the welfare of the animal. It is a response to internal stimuli (physiological) such as hunger or external stimulus, e.g. climate and temperature. If the goal of the action can not be achieved, the relevant behaviour may change [23]. Figure 10 shows the behaviour cycle of the animal.

In most cases, farmers are the main observers of the animal behaviour assessment. Therefore, the welfare status often depends on who and when the assessment is made. On the other hand, the involvement in these tasks would increase the demand for labours and the associated costs, which can affect the attention level for each animal. Thus, the traditional way of behavioural measurement is often subjective and may fail to notify potential risks over time [23].

Monitoring system deployed in the farm can consistently capture real-time images for investigation of animal behaviour and welfare states, in a quantitative manner, without the operators’ involvement. It can offer non-contact inspection and unbiased reports for the tasks. For this reason, the machine vision system is becoming the standard in food-related industries.

Such a monitoring system usually consists of hardware (camera, computer) and software. The hardware generates data to the programmed software to perform behaviour recognition tasks.

It is very similar to the human recognition process, in which the human eyes send visual data to the brain for interpretation and decision making [23].

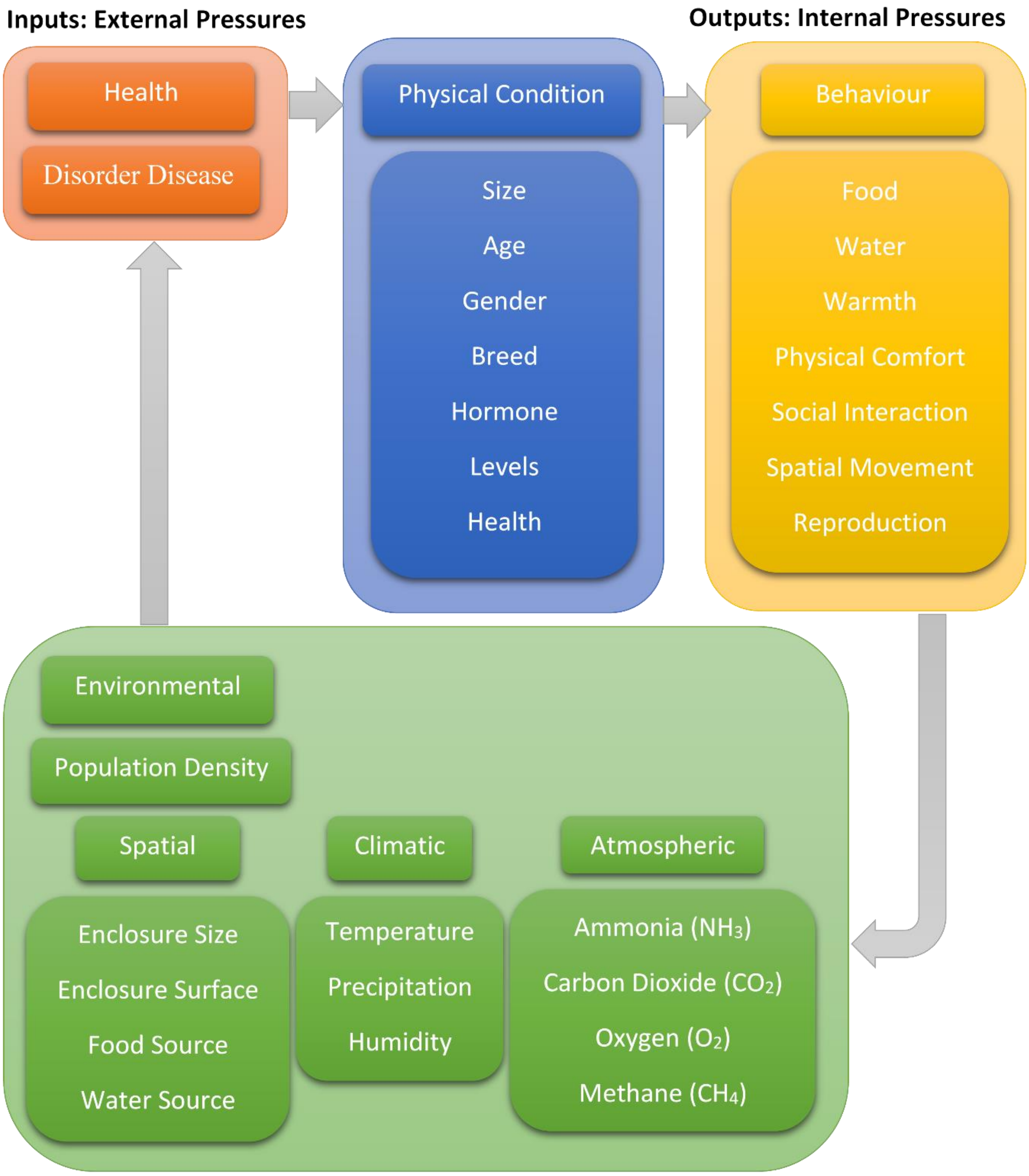

Figure 10 Animal behaviour cycle.

The behaviour recognition process can be divided into four steps as summarised in Table 2 as follows, where the recognition process is illustrated in Figure 11.

Initialisation	Configuration stage: all the hardware and software are to be ready for processing. Calibration for both hardware and software, data preparation.
Tracking	Segmentation stage: objects are identified and separated from the background. It can create associations between successive image frames.
Pose estimation	Identification stage: the state of the target object can be identified in an image frame.
Recognition	Successfully identifying the pose and correctly labelling it.

Table 2 Behaviour recognition process.

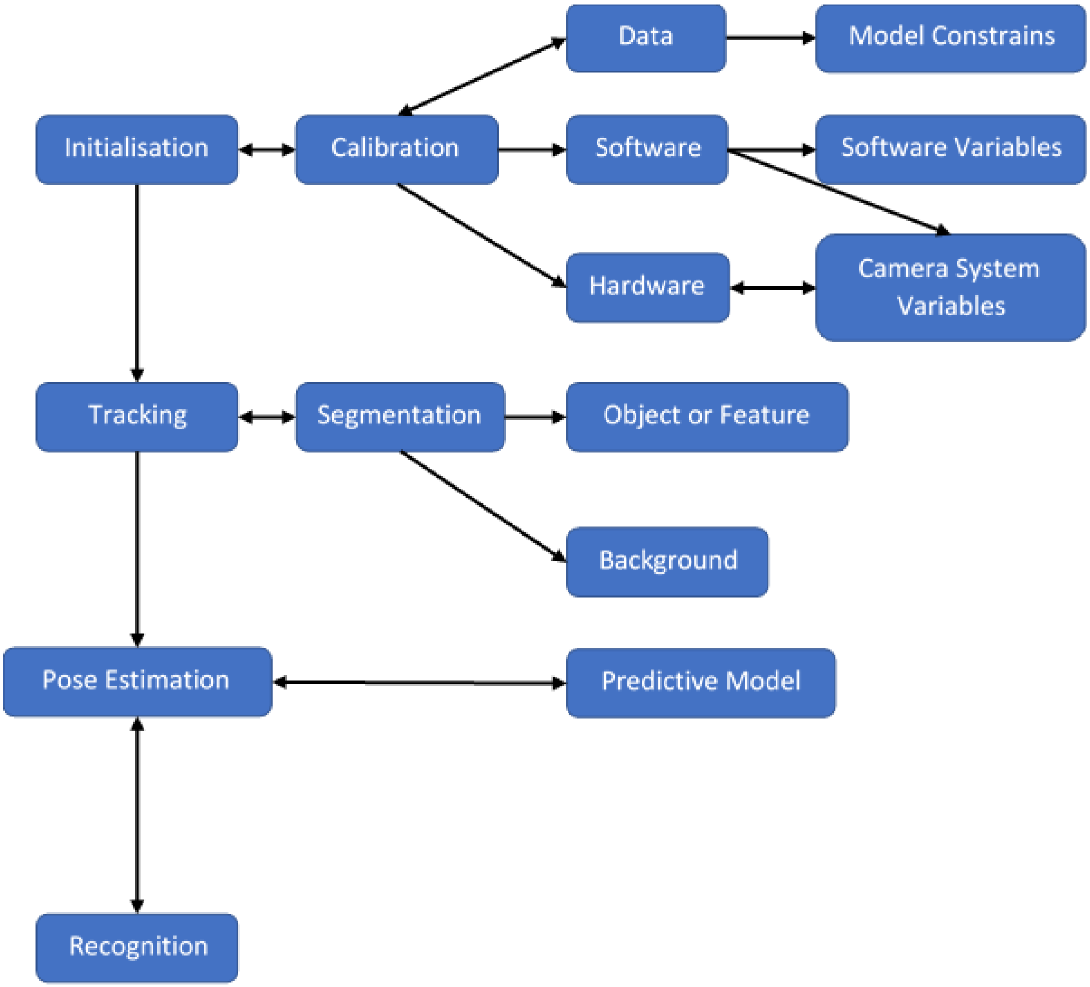

Figure 11 Recognition process.

2.4.1 Initialisation

The initialisation stage often involves hardware and software preparation before running the whole system. This can be performed either offline – before running or online – after running.

The calibration is the first step, such as changing the illumination of the environment and configuring the parameters of the camera, i.e. exposure time, focus and contrast. Well-tuned configuration can maximise the usability of the captured images, providing a good data source for further processing. This stage is often carried out offline. However, some equipment allows for on-the-fly modification. For example, automatic focusing is one of the built-in features in some cameras, which can adjust the focal length of the image sensor. ISO sensitivity indicates light sensitivity, and its dynamic change allows the image sensor to work better in low lighting conditions. Automatic exposure determines the correct exposure for pictures. These settings all contribute to improved image quality.

Other than the hardware initialization, the software running on the computer also needs to be carefully examined before running. Settings in the configuration files usually define the connection parameters to each camera and image quality related parameters for streaming from cameras and controlling parameters for image processing and tracking, they all should be examined before carrying out to the next stage.

The parameters which can describe the target object must be accurate enough for object detection. The parameter details can either come from a pre-defined model or, the system requires no knowledge of the pre-defined model. These parameters may need to be adjusted over time for tracking, clustering, and classifying of the animals [23][24]. The way that these parameters are configured has a significant impact on the overall performance of the system. In addition, the feature characteristic of the target object also plays a vital role [23].

2.4.2 Features and cues selection

In the monitoring system, accurately identifying the region of interest (ROI) and the target object is the key to model construction. For image data, we often define and extract a feature to represent the most significant characteristics of the image to distinguish these interested events and/or objects. We can combine multiple features to form an accurate model for further investigation.

The features extracted from the image can be classified into temporal, spatial, valued and textural types [23]. For example, by comparing the object’s position from two consecutive image frames, we can calculate the velocity and acceleration parameters of the object. Since we know the sampling rate or timestamp when the two frames are acquired, and if we keep tracking the travel distance for a whole day, the activity distribution among the day and the total amount of activities can be calculated for further statistical modelling and comparison. The velocity, acceleration, travel distance and overall activity are typically used temporal features. Spatial features include shapes of different size and dimensions that represent the volume and contour of the target object. Colour information in an image frame can be categorised as a valued feature, and it can be used to identify the target object or the background. In addition, textural features can be the combination of various features such as colour, shape, the temperature of the scene or object, and it could be a template of features.

Features included in the image are the primary source for identification, but we should also think of external sources, such as information from different sensors and environmental conditions. For example, illumination is an essential factor in nocturnal animals. They will exhibit differently according to whether the environment is 'light' or 'dark', and their activity varies depending on that [23]. Also, air temperature is another crucial factor that would affect animal behaviours, and it cannot be extracted from the image and needs to be acquired from a temperature sensor or real-time weather information. Other variables in the farm including noise level, air quality, feed and drinking station et al. all contribute to the animal behaviours, and these factors may affect the current condition and specific actions of the animal. Field observation of the animals could help us building the feature set more accurately, which would better describe the animal's behaviours.

2.4.3 Tracking

Tracking stage includes the segmentation and temporal correspondence processes.

Segmentation is to generate information to describe the target object by identifying and extracting the feature(s) from image frames. Usually, the result of the segmentation process is a group of features to represent the target object and associated other parametric measures of the target. Some pre-processing works can increase the accuracy of feature extraction, such as cropping the image to eliminate unexpected pixels or upsampling (downsampling) the image to change the image resolution et al.

Temporal correspondence is to find the correlation or correspondence between consecutive images. Features that appear in each frame can work as a footprint for establishing relationships with previous images. For example, extracting of position feature is vital in tracking because it can dramatically reduce the computing time in locating any feature of interests in subsequent images. The tracking process is fundamental in analysing the animal behaviours because the animal responses to a stimulus can often be reflected in their movements. By tracking their position changes and movements, we can draw a detailed picture of the movement path for helping us to accurately understand their behaviours. The responses to a stimulus may vary across different animal species, herd size, time of day, or even other associated conditions. This is a core component of the system for us to understand the welfare and behaviour of animals in farms [23].

Four techniques are often used in segmentation and temporal correspondence to extract features from images, as summarised in Table 3 below.

Scene-based	Use background-image as a reference and compare it with the updated image. If the background pixel is changed, indicating an object has moved or entered the scene.
Motion-based	Use temporal correspondence between frames to determine the movement of the object and extract some movement parameters such as velocity, direction, and acceleration et al.
Shape-based	Use shapes, edges, or points to rebuild the volume information of the object within the scene.
Appearance-based	For RGB cameras, we can use visual properties within the image, such as colour, intensity, saturation, and hue. For infrared cameras, we can get the temperature readings out of the thermal image. For depth cameras, we can measure the distance of the target object to reconstruct the 3D scene with Point Cloud data.

Table 3 Feature extraction techniques.

There is no strict order for applying those techniques to an image frame. Any sequence that can fit the model and speed up the computing process is feasible. For example, if we have thermal images, we can perform the scene-based technique to eliminate pixels below a specific temperature value. Usually, it is the floor that will be excluded from the image. After that, the shape-based technique can be applied to identify objects in the image, and even classifying them into categories or count them.

2.4.4 Pose estimation and behaviour recognition

The pose estimation and behaviour recognition stage determines the correspondence between a pose and the characteristic features of the target object, such as the shape, size, colour, and position etc. The appearance features can also indicate pose changes among certain species. For example, the inside of the bird's wing may have a different colour to its fur when it is still. Therefore, the colour feature can be used as a cue for this change. The behaviour recognition stage needs correctly locate corresponding features in the dataset and accurately cross-reference them in subsequent images [23].

2.5 Video Streaming

To fully achieve the expected performance of PLF, a robust monitoring system needs to be deployed in the farm and continuously run in a 24/7 mode. The system should be able to capture real-time images and send these to the software for further processing. This actually is the key to our goal of the generic platform. After the centre application has received the image frames, image processing algorithms can be applied to analyse target objects and interesting events, where relevant results can provide instant feedback to the operators and inform potential abnormal issues. For example, when animals are infected with a disease, their activities will decrease or increase than the regular rate. By recording their daily activity rate, we can compare such real-time information with the previous observations to build a disease forecasting model [25].

Video streaming is the transfer of video data from one point of an established connection to the other end [26]. In our case, the hardware (cameras and the computer et al.) will be deployed at the farm, and the software runs on the computer needs to be establishing a stable connection between them. At farms, the LAN network with the Cat5 cable is often used for this case, where the software can connect to the camera in a low latency mode for streaming images and sending commands for changing settings of the cameras.

To illustrate how such a system works, Figure 12 shows the design of the system. As seen, we have cameras mounted on the ceiling to monitor the pig behaviours and activities in each pen. The data will be fed to the computer for analysis and also transmitted to the mobile end for visualisation and interactions.

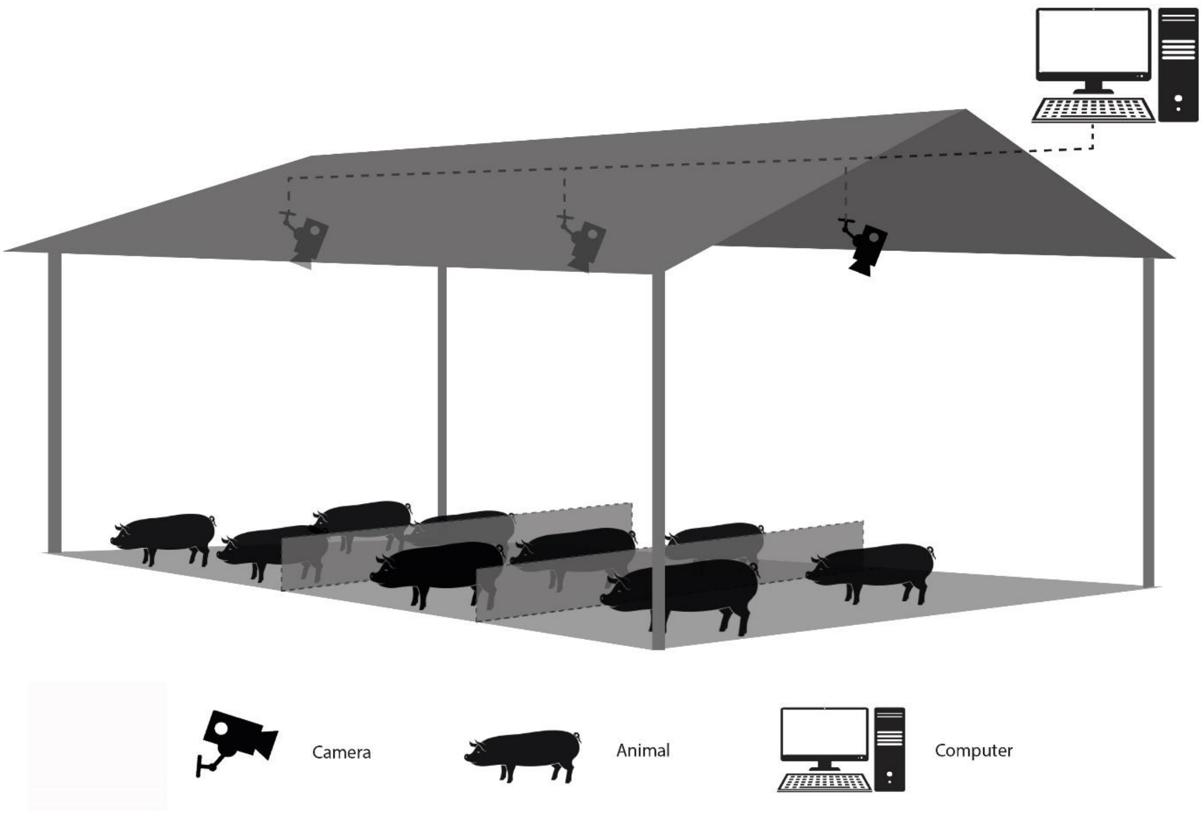

Figure 12 Platform design.

2.6 Precision Livestock Farming Applications

Table 10 and Table 11 in Appendix A summarised various machine vision applications developed for livestock farming. In these works, 2D and 3D cameras are used as an automatic and non-invasive way to monitor various characteristics of cattle and pigs in groups or individuals. Some works have tested in commercial farms and reduced workload of manual observations.

2.7 Summary

In this chapter, relevant background and related works for the development of PLF are introduced, including the technologies behind as well as the relationship between Smart Farming and PLF, and the factors which would drive this industry. Also, the core stages for building such a platform in terms of initialisation, tracking, pose estimation and recognition have been covered in detail, along with some key techniques for animal tracking. Many research works have been using these techniques in related fields. Based on the study, the PLF Platform can be designed, and the detail implementation will be introduced in the next chapter.

Chapter 3.

Generic Precision Livestock Farming Platform

At present, we are on the verge of a technological revolution, particularly owing to the emerging techniques and applications such as the IoT coined in 1995 [106] and advanced computing and communication [107]. Our platform can take advantages of this development by utilizing various sensors and devices, where detailed information about the surrounding environment can be digitalised. In fact, each device can contribute a piece of specific part information to the centralised software for building the integrated model. The software which connects to the sensors should be flexible and easy to use, able to easily extend the system by allowing a new type of sensor to be efficiently and effectively added into it.

In this chapter, the PLF Platform will be discussed in detail as follows.

3.1 Introduction

The generic platform consists of hardware and software. The hardware includes various sensors, cameras, and a computer. Those devices should be working in the same LAN network so that it can guarantee the stability and accessibility to each other at the farm setting. The software runs on the computer, which should be able to stream various types of data for processing.

3.2 Hardware

One challenging issue in choosing the hardware for livestock farming is the severe environmental condition. In order to make the device running 24x7, the hardware needs to be robust to liquids, dust or humidity which are pretty common in any animal farm. These requirements are often impossible for consumer electronic devices. However, the industrial component is designed for situations like this. It needs to be tested across different environments and obtained a rating for the degree of its quality to guarantee its high reliability than standard commercial components, especially being able to withstand different operating temperatures across a wide range.

Ingress Protection rating uses a two-digit code to denote the protection level of the enclosure. The first and second numbers represent the protection level against solid objects and water, respectively. The protection level at 0 means no protection, and levels 6-8 refers to about a full protection. Therefore, an IP68 rating completely prevents ingress of dust and protects against immersion in liquid up to 1 metre.

Table 4 shows the exact meanings of different levels of Ingress Protection (IP) ratings, where the desirable rating of devices for continuously running would be the highest one IP68.

Ingress Protection (IP) Ratings			
Solids		**Liquids**	
0	No protection	0	No protection
1	Protected against objects greater than 50 mm	1	Protected against dripping water or condensation
2	Protected against objects greater than 12.5 mm	2	Protected against dripping water when tilted 15 degrees
3	Protected against objects greater than 2.5 mm	3	Protected against water spray at any angle up to 60 degrees from vertical
4	Protected against objects greater than 1 mm	4	Protected against splashing water from any direction
5	Protected against dust, limited ingress	5	Protected against jets of water
6	Dust-tight, totally protected against dust	6	Protected against high-pressure water jets
		7	Protected against the effects of immersion up to 1 m
		8	Protected against immersion beyond 1 m

Table 4 Ingress Protection ratings (data from [131]).

- **Cameras**

IP camera is a specific type of camera that has its own IP address. It can be discovered once connected to a network. Some of them may equip with an embedded web server, FTP server, FTP client, email client, alarm management, and even programmability. We can establish a connection between the IP camera and the computer in the same LAN. Most of the IP cameras have built-in Real Time Streaming Protocol (RTSP) support, which can be used for streaming and controlling media session over endpoints. Also, to overcome the effect of severe working conditions, the cameras are normally asked to have the IP68 rating for surviving in animal farms.

- **Computer**

x86 computer can be used as the host machine for running our software at the user end. Other than the minimum system requirement, it has to have an enclosure or sealed case to protect the inside components from dust and water, because every farm keeps indoor cleaning by using a high-pressure water gun on the floor and walls in a regular basis. The IP68 rating is essential in this kind of premise setting.

3.3 Software Architecture and Implementation

Most farm premises located in rural areas may lack a stable internet connection. Remote capturing and transferring real-time data often require reliable internet connectivity. For a real-time system, it is impractical to send data to the cloud and process over there. The whole system needs to rely less on cloud computing and work independently. However, for safety and security reasons, all generated reports need to be sent to a remote server for further processing and centralised management.

The system will be subjected to intensive computation pressure, since image processing, the core part of the system, consumes most of the computing resources. In order to work efficiently, a low-level, close to the hardware layer programming language, would be suitable for our case. C / C++ is ideal for performance-critical task and computationally intensive applications. It has the ability to access various hardware. Moreover, the cross-platform nature of the language would allow deploying the final product in a lower hardware spec which potentially brings more selections as well as to reduce running cost on the hardware.

The general architecture of a monitoring system includes four main steps: initialisation, tracking, pose estimation and recognition [23][108]. We have expanded this architect in our case, as shown in Figure 13. The green graphs indicate the core modules of the software, which will be introduced in detail in the following sections.

After the Initialization stage, the software can 'talk' to sensors. Since the IP camera has built-in RTSP server, that allows the software to request the real-time video from it by sending RTSP request commands, the camera responds to the request commands and send back the encoded video stream to the software via an established TCP/UDP session. The received data has been compressed, needs to be decompressing and formatting in the decoding module. Data from other sensors need to synchronise prior to analysing, that is to prepare and combine all the data types that could guide the analysing module. Next, we can apply image processing algorithms to the frames. To do that, firstly, we can use predefined ROI to extract the interesting region, and the analysing module will first try to determine whether that region contains target objects or not (use segmentation techniques such as scene-based or shape-based to try to find the target objects). If it doesn't, drop the frame and return to the streaming module to process the next frame, if it does, the segmentation stage can use features and cues to extract detailed information of the target object within the image, such as shape, position, orientation and gesture. Further, we need to combine the analysed results with a piece of extra dimension information - time, to package this information and save it in local storage or remote database. The precise time when the data generated is a piece of crucial information for us to analyse the behaviours of target objects. Some works have been done by using consecutive images with daily animal activities to compare normal and abnormal behaviours, such as by analysing the gait of cattle to detect lameness among them [105], to analyse and predict pig locomotor and aggressive behaviour in the barn environment [109].

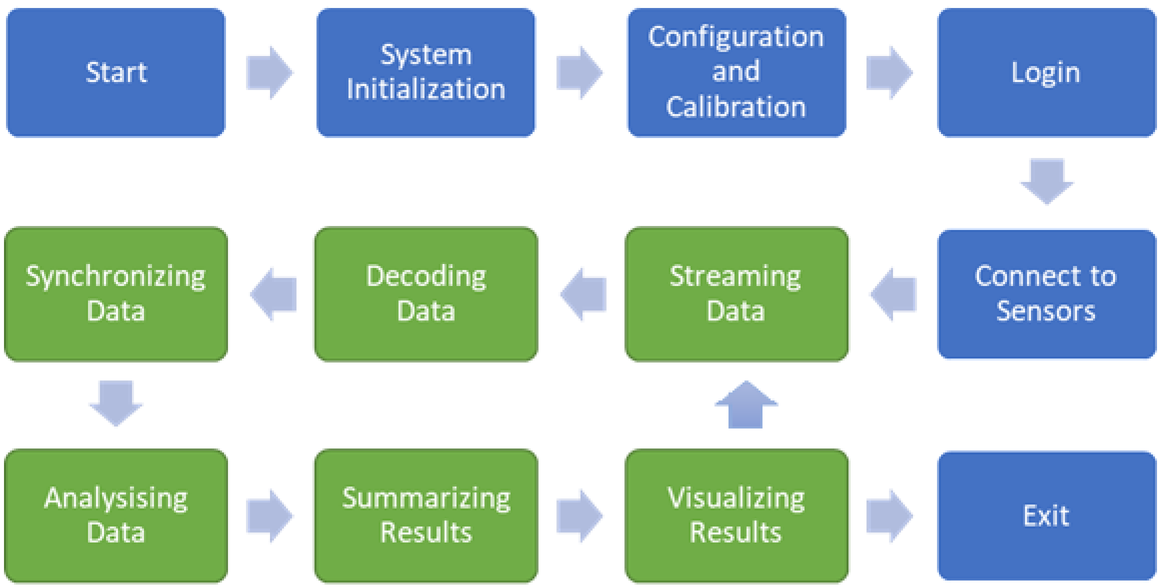

Figure 13 Workflow of the software.

The communication protocol between the camera and the software is the first step to implement the software platform. Generally, each camera manufacturer has its own Software Development Kit (SDK) and Application Programming Interface (API) to allow software applications to send commands to control the device. However, the commands often do not work for another manufacturer. To solve this challenge, a generic access layer which builds over different communication protocols is essential for making the system adaptive to different cameras as well as hiding all the implementation details in the sub-modules. The communication protocol will be introduced in the next sections.

3.3.1 Streaming

Steaming or retrieving data is a way of communicating between the main application platform and the sensors. The communication protocol used in transmitting datagram is often chosen by the corresponding data types and contents. Streaming video media is our main goal, and the most important point is to ensure low latency and low jitter during the operational running of the system. However, since the system is designed for continually running, occasional data loss is acceptable.

Push and Pull based streaming protocols		
Characteristic	**Push-Based**	**Pull-Based**
Source	Broadcast services such as Windows Media, Apple QuickTime, Cisco CDS/DCM	Web servers such as LAMP, Apache HTTP Server, Microsoft IIS, Cisco CDS
Protocols	RTSP, WebSocket, QUIC	IMAP, HTTP
Bandwidth usage	More efficient	Less efficient
Video monitoring	Widely support	Very rare
Multicast support	Yes, widely support	Limited support

Table 5 Comparison of push and pull protocols.

Media streaming protocol is defined according to the data structure of the content and the algorithms for sending real-time video data over the internet. There are different protocols available today, and most of them are just different in connection methods. In general, the two categories are push-based and pull-based streaming protocols [110]. In Push-Based Media Streaming Protocols, after the connection between the client and the server is established, the server-side starts to send data to the client until the session closed or interrupted. In Pull-Based Media Streaming protocols, the Client-side works actively and requires data from the server in an on-demand manner. Therefore, the corresponding responses are totally dependent on how often the client sends out the requesting messages. These two kinds of streaming protocols are compared in detail in Table 5.

Real Time Streaming Protocol (RTSP) is an application layer protocol that uses established sessions to communicate with endpoint devices. It is usually employed in entertainment and communication systems for controlling and streaming media. RTSP itself does not streaming data between devices. Rather, it uses User Datagram Protocol (UDP) and Transmission Control Protocol (TCP) for actual data transmitting tasks, where UDP is for data streaming and TCP for data controlling. The RTSP protocol is similar in some ways to the HTTP protocol.

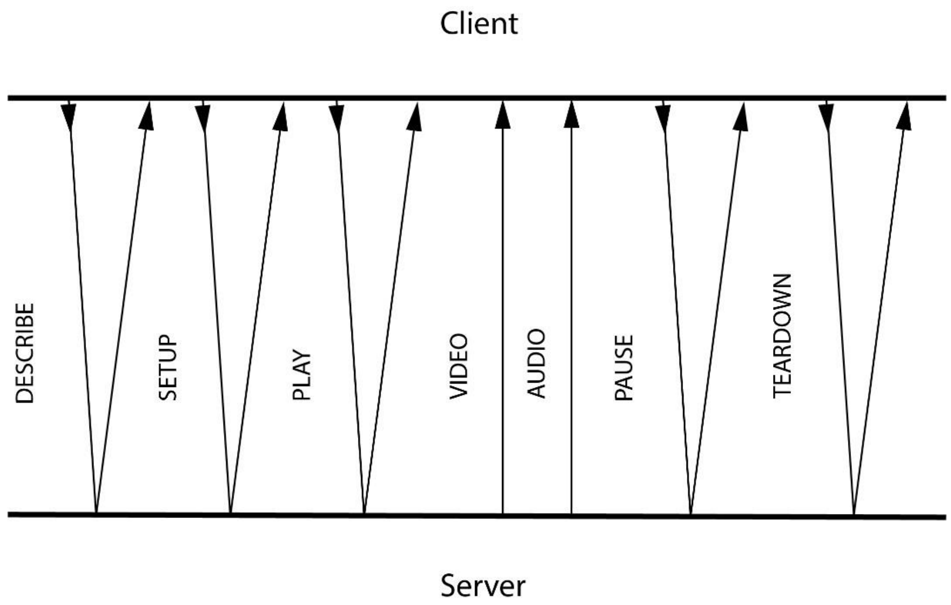

Figure 14 RTSP protocol workflow.

The URL structure for RTSP is represented by a “rtps://” header, other than that, it adds various controlling commands such as DESCRIBE, OPTION, SETUP, PLAY, PAUSE, RECORD, ANNOUNCE and TEARDOWN. The ‘DESCRIBE’ command is for obtaining the presentation description, and the request message is “DESCRIBE rtsp://IP_ADDRESS RTPS/1.0”. The server responds a Session Description Protocol format message with the information for initialisation of the connection and format information of the media streams. The SETUP command is for specifying how to transport the media stream. It usually includes a local port for receiving the audio and video data. The server responds a confirmation message to the selected parameters and fills in the missing parts such as the port number from the server. The DESCRIBE and SETUP commands must be sent before the PLAY command, as they are the initialisation and configuration of the media stream. The PLAY command requests the audio/video data to be played, which can be specified with a range or not, where the media will be played from the beginning to the end instead. The PAUSE command can pair with the PLAY command to halt and resume of the media. Finally, the TEARDOWN command can terminate the connection and release resources on the server. Other commands (such as OPTION, RECORD, ANNOUNCE) are not as important as these commands. As a result, these are not explained here. Note that, the RTSP often uses the default port #554 for connection and data communication [111].

3.3.2 Decoding

Decoding or format conversion is the process of converting the data from one sourced format to a desirable destination format. In this case, efficient transmitting of video data often requires encoding the source video with good quality but lower bit rates. A broadcast friendly with reasonable compression rate coding technique is needed for this task.

H.264 coding technique is the modern and most effective video compression standard, where high-quality video streaming can be achieved with low bit rates. It is perhaps best known as one of the video encoding standards for Blu-ray. The H.264 compressed video stream needs just 10% of the bandwidth as an MJPEG compressed video. However, H.264 video quality is approximately 95% of those compressed using the MJPEG [112]. As a result, this coding method has been widely used in many web videos services, such as YouTube, Facebook, and Vimeo. It has also been utilised in television broadcasting, Blu-ray low-latency video applications, visual surveillance, and web video etc. [113]. Figure 15 shows the bit rate comparison at the same level of image quality. The result showed that H.264 (baseline profile) encoder is the most efficient coding technique [112].

For implementation, FFmpeg is the main decoding library for the platform, which is popularly used to decode video streams. As a multimedia framework for video applications or even general purposes utilities, FFmpeg takes care of all the hard work of video processing by doing all the decoding, encoding, etc. in one framework. It supports the most popularly used formats and also highly portable, as it can be developed and tested across Linux, Mac OS X, Microsoft

Windows, BSDs, etc., under a wide variety of environments, machine architectures, and configurations [114].

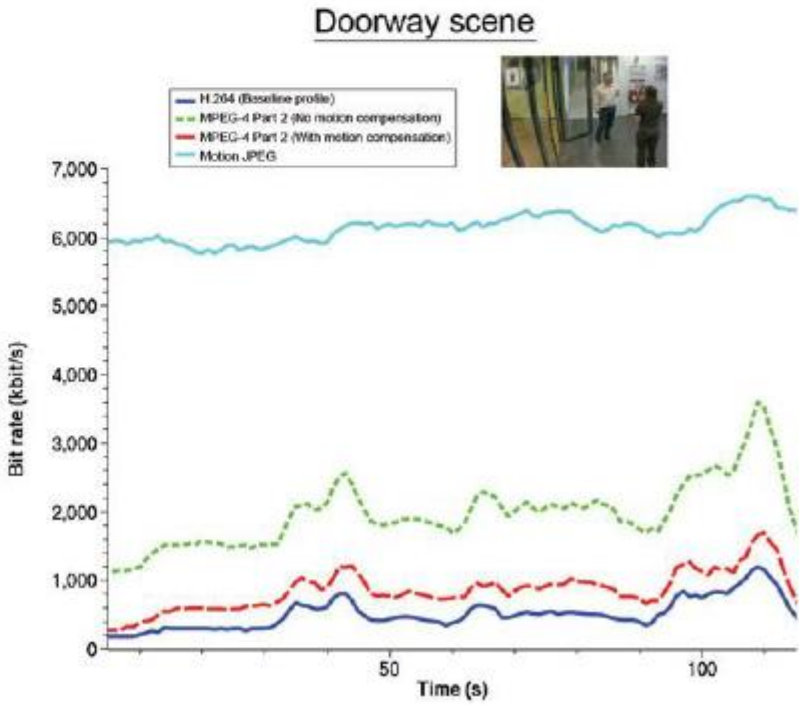

Figure 15 Bit rate comparison. (Image from [112]).

3.3.3 Synchronising

In a multiple sensor environment, each sensor represents a node and transmits data to the parent node (centre application) continuously. As data generated from different nodes are propagated towards the centre application, it is vital that the centre application can fuse such data as much as possible for increasing the credibility of the report. A fusion or synchronization process is needed at this stage prior to sending out any reporting data.

The synchronisation method often depends on the data types. For video data, one can combine every video frame with a variable time-stamp, indicating the exact time when the frame was generated. Adding this extra information will bring more evidence for the traceability of the scene. For example, if animals are fighting each other, the sudden increased volume can trigger an event and allow us to analyse the audio and video clips at exact the same time period. Another variable can also be associated with arbitrary data type is the geological information, which can tell the location of the generated data.

Note that, adding more variables on the fusion stage may put extra computing pressure on the analysing step. To tackle this challenge, the data needs to be refined. However, we still need to balance between fusion of extensive amount data and the latency incurred in the aggregation process to reach our goal of real-time analysis. If the data are unable or unsuitable to fuse at this stage, it still viable to pass on the data as long as it is uncorrupted. Since each sensor is designed to work independently, the add-on benefit of data fusion is important but not extremely necessary.

3.3.4 Analysing

The general concepts and related work of feature extraction and cue selection have been discussed in sections between 2.3.1 and 2.3.4. Note that the identification of features in image frames needs to consider the cost, that includes the cost of time, money, and energy. In practice, it needs to meet the demand in terms of the expected accuracy and the computational cost. These processes must be capable of locating the target object such that object referencing can occur reliably, where false detections can also be minimised in the subsequent recognition stage [23][23].

3.3.5 Summarising

Summarisation is an optimisation approach for reducing noise among the extracted feature sets. Due to unexpected interruption occurred during the operations such as dropping frames, illumination changes, and shadow. The credibility of image frames can be severely affected. It is quite a challenge to match all features within a single frame correctly. However, the combination of a series frames could increase the reliability of the result and reduce the number of false detections. For example, locomotion tracking needs to get the location, orientation, velocity, and acceleration features of the targets by comparing the changes in the target objects in consecutive frames. We could attach an estimated variable to each feature based on their previous trajectory. The estimate can be kept updating by comparing the newly observed results with our estimations after the system resumed, where we can decide whether to accept those estimations or not.

3.3.6 Visualising

Visualisation is part of the system which provides a human-friendly way of viewing the analytic results in a diagram fashion. We can use web technology to show results on browsers such as Google Chrome, Firefox in keeping with our platform-independent goal.

There are two approaches for web-based technologies, HTTP pooling and WebSocket. HTTP Polling consists of a serial of request-respond pair messages to communicate between the server and the client. Since the HTTP is stateless exchange protocol, the client needs to actively ask for the desired information constantly. One could notice that real-time displaying of information will put enormous pressure on the server-side. Since the client does not know when the data have been updated, thus, it needs to repeatedly request for updates. The server responds with a new message if there is one, or with an empty response if no new message is available for that client. This technology can work well for a static webpage but not for real-time information display.

Another variation of HTTP Polling is Long Polling, in which the server holds the connection open for the client in a fixed period of time. If a new update message is available during the time period, the server will send the new message. Otherwise, the server will terminate the connection and clean up the resources. This reduces the number of responses to the client when there are no new messages. However, it cannot provide a substantial improvement over traditional polling [116].

WebSocket is a bidirectional communication protocol standardised in 2001, which operates through a single socket connection [117]. It does not involve additional request-respond headers for communication. Besides, the full-duplex connectivity allows transmitting data at the same time from both sides without unnecessary overhead. The most significant benefit of WebSocket is it will dramatically reduce network throughput and latency involved in real-time web application.

In comparison to network throughput and latency [116], it tested the performance of HTTP polling and WebSocket, as detailed in Table 6 and Table 7. On each test case, every client requests updating the data in 1 second interval.

As can be seen in the comparison results in Figure 16, WebSocket can dramatically reduce the network traffic. One reason is that the HTTP has enormous overhead in data transmission, especially the requests and responses header. The situation will be much worsened when the data needs to be updated frequently.

HTTP Polling			
Test case	**Case A**	**Case B**	**Case C**
Client number	1000	10000	100000
Network traffic	6.6 Mbps	66 Mbps	665 Mbps

Table 6 HTTP polling performance test (Data from [116]).

WebSocket			
Test case	**Case A**	**Case B**	**Case C**
Client number	1000	10000	100000
Network traffic	0.015 Mbps	0.0153 Mbps	1.526 Mbps

Table 7 WebSocket performance test (Data from [116]).

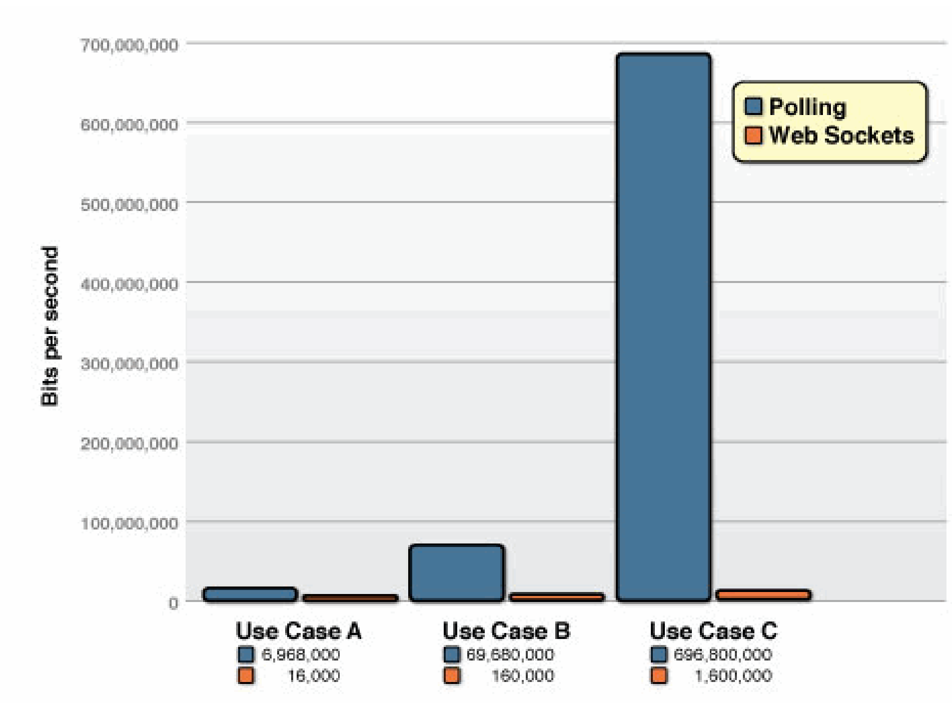

Figure 16 HTTP Polling and WebSocket throughput comparison (Image from [116]).

Figure 17 shows the workflow of the HTTP Polling and WebSocket. As can be seen in the top half of the figure, the half-duplex HTTP Polling introduced a lot of extra latency in transmitting the data. Assume it takes 50ms for a message travels from one side to another, the HTTP Polling requires extra requesting messages from the browser to be sent to the server.

In the bottom half of Figure 17, the WebSocket can significantly reduce the latency. Once the connection is established, the data can be sent to the browser the moment they arrive, i.e. with almost no delay. The WebSocket connection remains open between the browser and the server, so no additional requesting messages are needed in data transmission.

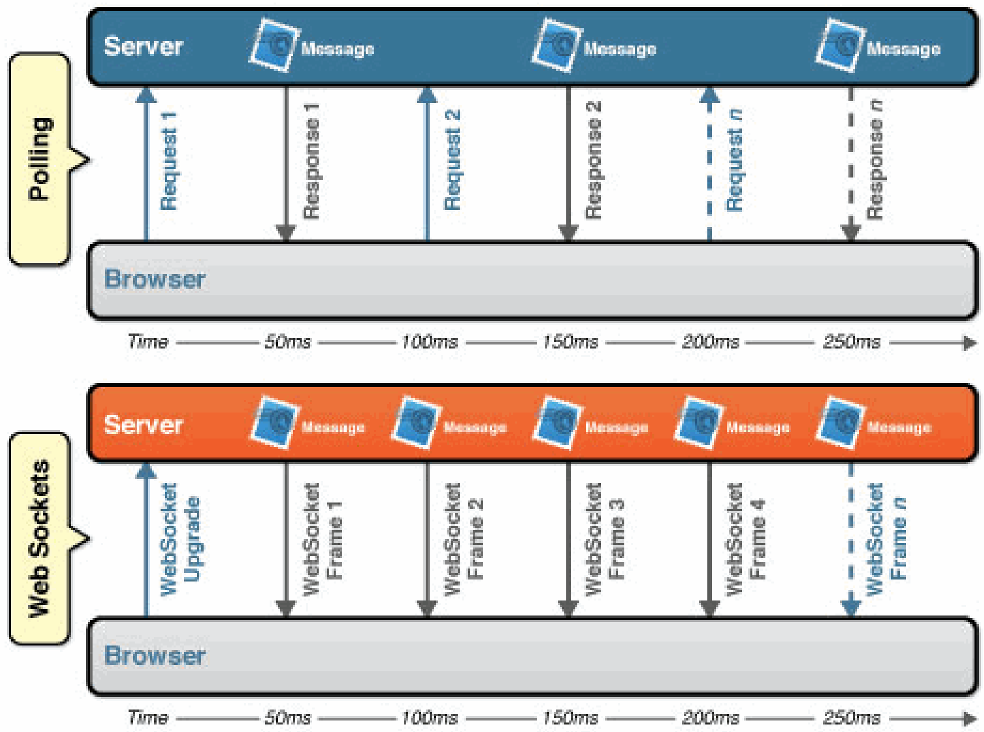

Figure 17 HTTP Polling and WebSocket latency comparison (Image from [116]).

3.4 Summary

In this chapter, we have presented the core technology stacks in developing this platform. Some modules have multiple implementation options, the one we have chosen for is based on functionality, the efficiency of the running cost and cross-platform performance. Employing modern technologies has helped farmers to wisely allocate their time and energy on daily activities. By collecting and analysing vast quantities of data, PLF can provide stakeholders with real-time information on animal's growth conditions and welfare status.

Chapter 4.
Tracking and Behaviour Recognition of Pigs

4.1 Introduction

The internal body status and conditions of the animals can usually be reflected through their behaviours. Hence sudden changes in their behaviours can be used as a sign of early warning of some health or growth related issues or problems. For identifying any potential issue or risk, one biggest challenge is to accurately locate the animal within the group [118]. To date, manual observation is still the only method applicable for most farms to identify the compromised animals. However, given the large number of animals in a modern farm setting, it is an extremely challenging task to inspect and score every animal even once a day. Other than that, the condition rating of each animal is highly subject to the farmer's opinion, which may vary significantly and become very biased due to the difference in their personal experience.

The current pig industry is operating with a piglet loss rate of 20.8% from birth to weaning. In addition, the industry is dealing with the devastating impact of viruses and bacteria such as Porcine Reproductive and Respiratory Syndrome (PRRS), Porcine epidemic diarrhoea (PEDv) and Porcine circovirus associated disease type 2 (PCV2). PRRS alone is estimated to result in an annual loss of $664 million to the U.S. alone [119]. The outbreak of African swine fever (ASF) in China was more devastating. Since the first detected case from China in August 2018, it has wiped out more than one-third of the pork industry, leading to a direct loss of over $140 billion [120]. This is partly due to the reason that intensification farming is more prevalent in modern livestock farming. Diseases are more easily transmitted among pigs and worsen the situation. Adding all these aspects together, this also indicates that early identification and treatment can yield substantial benefits to farmers and producers. In this chapter, the application of the PLF Platform will be introduced, as a case study of applying the developed generic platform to a commercial farm premise, for tracking and behaviour recognition of pigs.

4.2 Background

In recent years, many researchers have demonstrated by using non-invasive and automatic methodologies for consistent assessing animal's conditions. Among those works, the 3D camera has been gaining increasing popularity in livestock farming applications for automatic pig monitoring such as weight detection, feeding and drinking monitoring, lying, locomotion and lameness behaviour detection.

3D camera uses the ToF technology to determine the depth of the surrounding environment and generate depth information of the measurement. It is relatively inexpensive and accurate compared to other 3D depth scanning technologies such as the structured light and LiDAR. Figure 18 shows as an example a depth image captured from a 3D camera installed at the roof of a pig pen.

Figure 18 Depth image captured in a pig pen.

The PLF Platform is formed by the hardware and software parts. The hardware system includes a depth camera, PC (i7, 8GB RAM, x64), and 4TB hard drive. The depth camera captures depth images at a frame rate of approximately 7 frames/sec with a spatial resolution of 320x240 pixels. Prior to the start of the test, a manual configuration of the camera's working range was set to 4m, which covers the height from the camera to the floor. The depth camera was mounted above the pen and connected to the PC via a Cat5 Cable. The PC was put inside closure and installed outside of the pen and connected to the Internet. All hardware devices and cables can resist high-pressure cleaning water and moisture with an IP68 rating.

The software part, which is the intelligent part of the whole platform, needs to be streaming the live video frames from the camera, decoding the frame, applying algorithms for extracting valuable information from the frame, and finally, visualising the result.

Chapter 2 and 3 have demonstrated the technology stack, and this study is based on preliminary research with the Innovent QScan System [7][130], though the framework has been much improved for reliability and robustness.

4.3 Method

For tracking and behaviour recognition, the animal objects need to be detected first, followed by object tracking and behaviour recognition. Object recognition includes background detection, object detection and object classification. The output of the object recognition will be the input source for tracking and behaviour recognition process.

4.3.1 Background detection

With the camera installed on the ceiling of the pig pen, the first step is to define a valid range for producing the depth image frame of the maximised contrast. Herein, we set the minimum and maximum threshold value of the depth information for each pixel to exclude pixels outside the scope. The equation below shows this process.

$$G(i,j) = \begin{cases} 255 & , \quad D_{min} \leq d(i,j) \leq D_{max} \\ \dfrac{d(i,j)}{16} & , \quad otherwise \end{cases} \tag{1}$$

Where $G(i,j)$ is the new depth value, and $d(i,j)$ is the depth from the camera. D_{max} and D_{min} are the maximum and minimum depth threshold from the ceiling. Usually, the D_{max} should be selected a few centimetres higher above the floor for excluding pixel comes from the floor and the D_{min} should be higher than the maximum height of any standing pig. So only depth information comes from pigs can fit in our height range, normally the ignored pixels are grey.

In some cases, the raw depth data captured by the camera may contain values of NaN (Not a Number) which is because of the ToF sensor within the camera could not obtain the signal's return pulse in time, or the noise in the environment affects the pixel generating process. NaN can be a problem of pixel manipulation; any arithmetic operation with NaN will output invalid data. Pre-process of each pixel is necessary at this stage to ensure that the depth frame can only have valid depth value.

Figure 19 shows the result of this process. The camera is installed on the ceiling at the height of 2615mm, the threshold values for D_{max} and D_{min} are 2500mm and 1800mm. After this process, depth values outside and inside these thresholds are represented by grey and white, respectively.

Figure 19 Background detection.

4.3.2 Object detection

After thresholding based background detection, the white regions represent objects above the floor and below the maximum height. To extracting the objects in the white regions from the image, it is important to choose a suitable value for further thresholding. Usually, the histogram has two peaks, representing respectively the object and the background. Hence the suitable value of threshold can be found at the bottom of the valley. However, it is not easy to select the bottom precisely because the valley could be flat or the two peaks are utterly different in height [122]. Otsu's method is a process of automatically determining an optimal threshold to separate the foreground and background pixels, especially for images with two peaks in the histogram. It is based on a very simple idea, i.e. to determining the threshold that minimizes the weighted within-class variance. It is the same as maximizing the between-class variance [123]. After applying Otsu's method to the image, different regions, actually 27, can be extracted from the image, where some of those regions are expected to be pigs. Figure 20 shows the detected regions in different colours after this process.

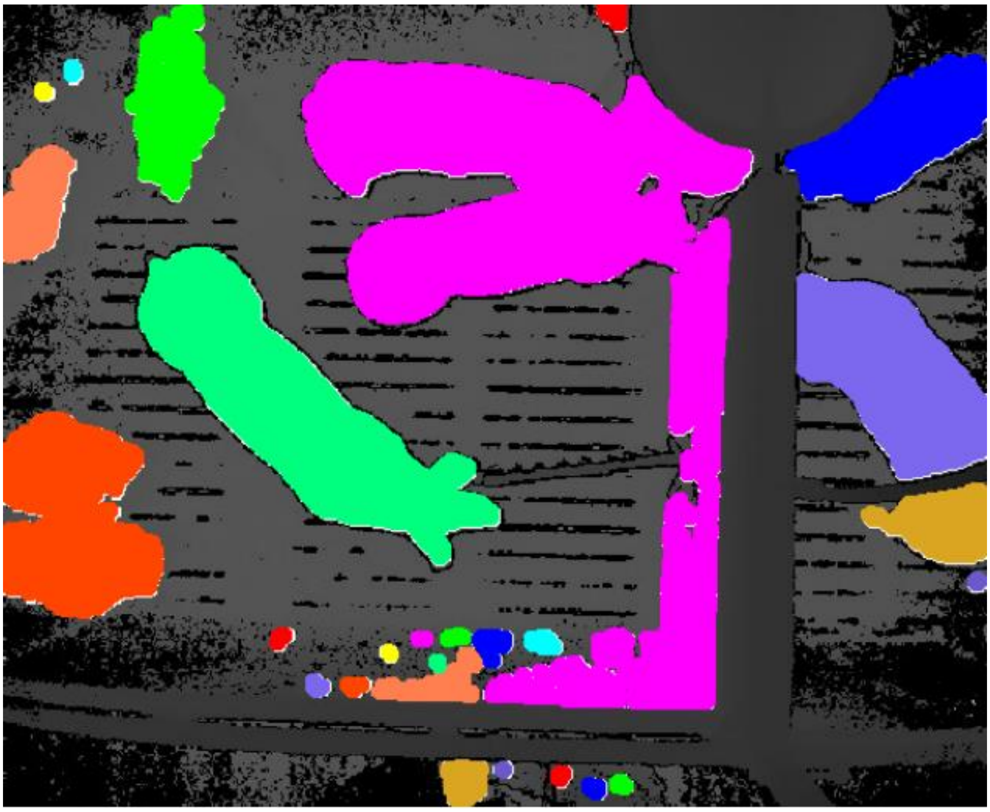

Figure 20 Object detection.

4.3.3 Object classification

After object detections, regions with various shapes and size can be extracted from the images. In imaging processing, shape, as one of the appearance properties of the object, is a powerful feature for describing and differentiating the objects. Often object classification can also be completed by making decisions based on the geometric properties of the object [124]. In our case, several different shape metrics such as circularity, rectangularity, main radius and anisometry are applied to each region for determining the geometric properties of the object.

1) Circularity

To calculate the circularity of a region, assume S is the area of the region, and the maximum radius distance M is obtained by measuring the distance from the regional centre to the outermost pixel of the region. Thus, we could obtain the circularity C as follows [124]:

$$C = \min\left(1, \frac{S}{M^2 \times \pi}\right) \tag{2}$$

The circularity result of 1 indicates the region is a circle, or non-circular results less than 1.

2) Rectangularity

To calculating the rectangularity of a region, a rectangle can be determined if the original region has the same first and second order central moments [125]. Let the area of the original region be A_1, the area of the determine rectangle be A_2, and the area of the overlapping part be A_3. The rectangularity is defined as [124]:

$$R = 1 - \frac{A_1 + A_2 - 2A_3}{A_2} \tag{3}$$

The rectangularity of a regular rectangle is 1. The more the region deviates from a regular rectangle, the less rectangularity value will be.

3) Main Radius

As the definition of the central moment, the main radius is calculated by [125]:

$$r_a = \sqrt{2\left(M_{20} + M_{02} + \sqrt{(M_{20} - M_{02})^2 + 4M_{11}^2}\right)} \tag{4}$$

$$r_b = \sqrt{2\left(M_{20} + M_{02} - \sqrt{(M_{20} - M_{02})^2 + 4M_{11}^2}\right)} \tag{5}$$

where M_{20}, M_{02}, and M_{11} are the central moments of the region, r_a is the main radius and r_b is the secondary radius.

4) Anisometry

The anisometry of the region is simply defined as the ratio of the main radius over the secondary radius, which stands for the aspect ratio of the region.

$$Anisometry = \frac{r_a}{r_b} \tag{6}$$

5) Region's centre

The depth information generated from the camera often contains noise pixels around the outer edge of the image. That means the pixel information in every frame could be different even at the same position. 'Chop off' the outermost side of the image by a few pixels could reduce the risk of false detection. To do so, simply by defining an ROI (region of interest) of a valid region centre and remove the noise pixels.

4.3.4 Target selection

The shapes of the detected objects can be classified into different categories based on their geometric properties. In our case, the shape of a pig captured from a top-down camera is more likely to be an ellipse. Table 8 shows the derived measurements from the aforementioned metrics.

Valid Parameter Ranges		
Filter	**Min Value**	**Max Value**
Circularity	0.15	0.35
Rectangularity	0.65	0.85
Main radius	80	1000
Anisometry	2.5	4.5

Table 8 Filter parameters for pigs.

Note that in Figure 20, smaller regions may pass all the filters. However, we could not recognise them as pigs because of their small sizes. As a result, we can simply exclude these tiny objects with an additional constraint on the sizes to minimise false detection. After applying this, standing pigs in our desired threshold can be selected, as shown in Figure 21.

Figure 21 Target selection.

4.4 Tracking

After the object detection, we can output all the detected target objects, in our case, the pigs. Each object will have associated properties such as the coordinates (x and y represent the relative position to the ROI), height (absolute height in pixels), shape (circularity, rectangularity, main radius, anisometry), and area (real-world size of the contour).

For tracking pigs, the camera can be taken as a radar system. It scans the environment and produces an image of the pen at a relatively fixed time interval. As pigs can be detected in the image, the properties associated with the pigs can be extracted and used as parameters for object tracking. Alpha-beta filter is one of the tracking methods being used in our implementation, which is actually closely related to the Kalman filters [126]. The main advantage of the alpha-beta filter is model-free, which does not require detailed knowledge of the system. In the simplest form, it maintains two internal states of the system – estimated state and observed state, where the estimated state adjusts itself by the value of the observed state over time [127]. Figure 22 shows the workflow of this method.

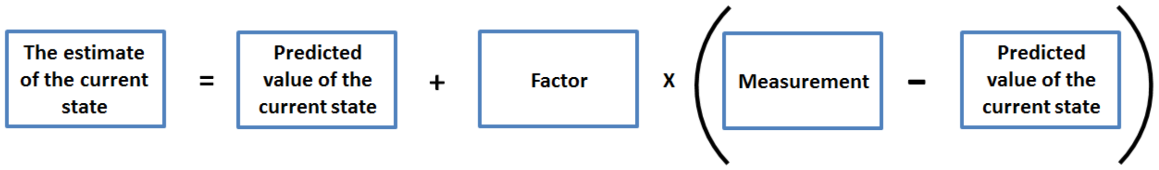

Figure 22 Alpha-beta filter.

In our case, the camera runs at 10 frames per second, so the ΔT in between frames is relatively small. Thus, we could assume that the overall velocity of the pig remains unchanged between measurements. The position state of the pig is then obtained by:

$$\hat{x}_k = \hat{x}_{k-1} + \Delta T \times \hat{v}_{k-1} \tag{7}$$

The velocity state v is presumed constant between two frames:

$$\hat{v} = \hat{v}_{k-1} \tag{8}$$

Normally, the estimated position will deviate from the actual observation, that is due to noise, and dynamic factors are ignored by this filter. However, the residual r is often used to compensate for the deviation of the estimation [127].

$$\hat{r} = x_k - \hat{x}_k \tag{9}$$

The alpha-beta filter takes the selected $alpha$ and $beta$ constants and uses $alpha$ times the residual r to correct the position estimation. For correcting the velocity estimation, the ΔT needs to be taken into account as follows:

$$\hat{x}_k = \hat{x}_k + \alpha \times \hat{r}_k \tag{10}$$

$$\hat{v}_k = \hat{v}_k + (\beta / \Delta T) \times \hat{r}_k \tag{11}$$

Here, the values of $alpha$ and $beta$ are often selected according to the movement characteristics of the object. In general, fast moving objects are better to select a larger $alpha$ and $beta$, because it has more tolerance in a sudden change of position while tracking the objects. On the other hand, a smaller $alpha$ and $beta$ can reduce the deviation between the estimated state and the observed state. Appendix B shows the general implementation of the alpha-beta filter in C language.

4.5 Behaviour recognition

Lying behaviour often reflects the animal's response to the room temperature. In a high temperature room, pigs tend to lie down and avoid physical contact with others, so they can transfer as much heat as possible to the floor. At a low temperature, they tend to stick together to reserve energy.

The detection result of lying behaviour has been used as an indicator for adjusting room temperature [37][83][130]. In our case, the lying detection is accompanied by a tracking process, where the Otsu's method has excluded objects unlikely to be pigs. The remaining objects, which are assumed to be real pigs, have properties such as shape and area that can be used for lying behaviour detection.

First, a reference image needs to be generated. To do so, we record multiple consecutive images as the input images and calculate the median value for each pixel. The median values are the pixel values of the reference image at the same position, and the reference image is used to subtract between the input image and the reference image. The resulting image is the subtraction result between those two images, and it usually has noise pixel values because of the inconsistent depth information. To exclude the noise pixels, objects which fail to satisfy the initial thresholding and the following on object detection as valid pigs are simply ignored. The resulting image with shapes similar to pigs is preserved.

The pixel value of the resulting image means the distance to the floor. Lying pigs are more likely close to the floor, and their pixel values are smaller than standing pigs.

Figures 23-25 show the images and the corresponding results.

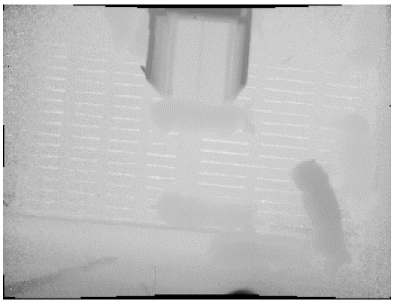

Figure 23 Source Image.

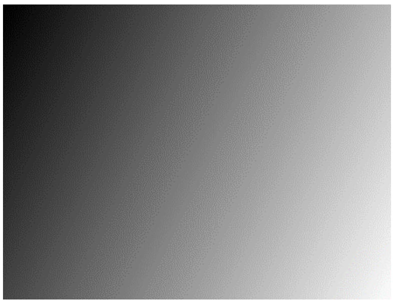

Figure 24 Reference Image.

Figure 25 Result Image.

As seen in the resulting image in Figure 25, there are 4 detected objects believed to be pigs. By comparing the average pixel value of the target object, the pixel value between the lying pigs and the floor is between 65 to 150, and the pixel value between the standing pigs and the floor is within 350 and 440. Therefore, we use 200 as the threshold to detect lying pigs.

4.6 Results

In this study, we recorded 350 consecutive images with less grouped activities among pigs. There were in total 1682 times that pigs have appeared in the images, in which pigs are found lying on the floor in 909 times and in the remaining 773 times the pigs are standing in the image. All these are manually labelled as ground truth for quantitative comparison.

Detection Performance Comparison			
Recognition Method	**Detection Count**	**Error rate**	**Accuracy**
Object Recognition	1591	5.41%	94.59%
Lying Recognition	823	9.46%	90.54%
Standing Recognition	768	0.65%	99.35%

Table 9 Recognition Comparison.

For detection of pigs, there were a total of 1591 times, in which the pigs have been recognised accurately with only one false-positive recognition. For the behaviour recognition accuracy of the pigs, there were a total of 823 times that the pigs have been recognised as lying down with 1 false-positive recognition. For standing pigs, there were a total of 768 times. Table 9 shows the result of detection and behaviour recognition.

4.7 Summary

In this chapter, we applied the developed generic platform in a commercial pig farm and introduced in detail how the system works, especially for the object detection and behaviour recognition. First, we excluded pixels outside the valid ranges and cropping a few pixels along the edges of the image to get a clean source image. Then, Otsu's method is used to extract foreground objects from the source image. To find out the geometric properties of the objects, we applied several shape related filters to determine whether the object is a shape of a pig. Afterwards, the remaining objects are detected as pigs, and corresponding features are extracted for object tracking and behaviour recognition.

We used the alpha-beta filter for tracking animals because of the animal's position features often changed linearly. The alpha-beta filter estimates a prediction position which compares to the observation position to determine the actual position of the animal for updating the estimation model accordingly. The general implementation of the alpha-beta filter is given in the appendix B section.

For behaviour recognition, in our case, determining lying and standing behaviours requires a ground image as the reference image. The value of each pixel in the ground image is the median value from multiple images for robustness. Hence, the pixel value of the subtraction result between the source image and ground image is the height distance to the ground, which can be used to determine whether the animal is lying or standing.

In our study, both the segmentation based detection and behaviour recognition have achieved a quite good accuracy rate. Automatic monitoring and analysing can release a huge amount of labours in daily warfare assessment work in commercial farms.

Chapter 5.
Conclusion and future work

This chapter summarises the conclusions that can be drawn from the work presented in this thesis, along with some ideas provided for further research and development.

5.1 Conclusion

In conclusion, PLF has proven the capability in helping farmers to improve the welfare and productivity of the animals. They can once again treat their animals as individuals rather than a herd, and the data generated during the growth cycle would provide tremendous information for feeding companies, veterinarians, and processing companies. A further step would be sharing data to consumers which may lead to new approaches in food branding.

The major contributions of this thesis and several technical tips for developing the platform can be summarised as follows:

- **Steaming protocols and decoding methods.**
  Chapter 3 has introduced different protocols for streaming images from the cameras. Although manufactures often have different APIs for developers, a standard streaming protocol with RTSP technology is recommended as the best option for streaming RGB images. The image data received are usually compressed and need to be decoded again using the FFmpeg prior to any further processing. We also have compared the compression ratio and performance of FFmpeg.

- **Fusion of external data source.**
  The general architecture of the monitoring systems is presented, which includes four main stages. As for our case, different types of sensors and data can be fused to maximise the potential of PLF. Therefore, we have introduced a fusion module into the software architecture. As data generated from various sensors are propagated towards the centre application, it is vital that the centre application can fuse the data as much as possible for increasing the credibility of the report. This module can add more intelligence to the associated analysis software.

- **WebSocket based technology for visualization.**

  Visualization is always an important part of the monitoring system. Cross-platform visualisation of the images often depends on the web technology, fro which two approaches are often employed for web-based technologies, i.e. HTTP pooling and WebSocket. We have compared the details of these two technologies as well as the performance, based on which, we have identified that WebSocket is the most reliable protocol in terms of data transmitting for web applications.

- **Depth image processing.**

  A case study application of the generic platform with the TOF camera is introduced in chapter 4. The camera needs to pre-configured based on the installation scenarios as well as the working range for accurate distance measurement for 3D reconstruction and mapping of the scene. Converting the pixel value requires to take care of the NaN values in case of invalid data.

- **Animal tracking.**

  In chapter 4, the alpha-beta filter is introduced for object tracking. First, we applied the Otsu's method on objects to filter shapes similar to pigs, followed by the alpha-beta filter for object tracking. In 300 images manually labelled for each pig, the detection accuracy is 94.59%.

- **Behaviour recognition.**

  After successful detection and separation of the objects from the background, quite a few metrics, including the height of each object are measured. Considering that the pixel value between the lying pigs and the floor is within 65-150, and the pixel value between the standing pigs and the floor is between 350 to 440. We set 200 as the threshold to separate lying pigs and standing pigs. The results of differentiating lying pigs and standing pigs are 90.54% and 99.35%, respectively.

5.2 Future work

The value of this technology is dependent on its adaptability to a wide range of sensor technologies while transforming the data to the semantic outcome to guide the process of smart farming. Thus, the capabilities of integrating different types of sensors and data processing are important.

Different camera manufacturers often have their own APIs for data acquisition, a generic way of accessing the captured image data is to encapsulate the streaming module into a sub-module in order to provide a generic access layer to the data. This can hide the implementation detail across different APIs without changing the general workflow. The same approach also applies to other IoT devices.

The accuracy of object detection and behaviour recognition can be further improved. Animal's behaviours are often unpredictable, and they usually tend to stick together according to their habits. Most research, including this one, does not handle segmentation in very high accuracy. Tightly grouped animals are usually ignored in processing because of the difficulty of separating touching objects properly. The main reason is the software does not have 'presence' of the environment information, and the source image is the only input knowledge. Reconstruction of the environment prior to processing is a way to reduce the reliance on the input data. For example, once a moveable object has been detected, the tracking resilience on that object can be increased. When the object is grouped with others, i.e. the segmentation process fails, this change can be noted, and thus further arrangements can be scheduled as a backup solution. This works well when a pig is lying down on the floor when another one is passing through above it. The software can understand there was a lying pig when a collision is happed. To this end, the image data is not the priority knowledge at that time.

Further development on the individualisation of each animal can be achieved, possibly by adding the RFID technology to the monitoring system. RFID reader placed in the scene can be predefined in the system. Any entry to the reader's detection range can trigger a single response with a unique ID of the animal's tag. The system would just need to find the nearest animal to the reader and establish the link. This platform has reserved the data fusion module. With adequate hardware, this method can be implemented for improved reliability and functions.

Consistently collecting information on each animal is an important step in unlocking the potential of PLF. A further step would be to share the collected data with end-users of the value chain – consumers. This can help their buying decisions based on farmers' practice, whilst farmers can also optimise their production strategies based on the preferences from the consumers' side. This will be the most beautiful thing about PLF.

References

[1] Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming–a review. Agricultural Systems. 2017 May 1;153:69-80.

[2] Guarino M, Norton T, Berckmans D, Vranken E, Berckmans D. A blueprint for developing and applying precision livestock farming tools: A key output of the EU-PLF project. Animal Frontiers. 2017 Jan 1;7(1):12-7.

[3] Morota G, Ventura RV, Silva FF, Koyama M, Fernando SC. Machine learning and data mining advance predictive big data analysis in precision animal agriculture. Journal of Animal Science. 2018 Apr 14.

[4] Food and Agriculture Organization. How to Feed the World in 2050. InExecutive Summary-Proceedings of the Expert Meeting on How to Feed the World in 2050 2009 Oct 12. Rome, Italy: Food and Agriculture Organization.

[5] Kendall H, Naughton P, Clark B, Taylor J, Li Z, Zhao C, Yang G, Chen J, Frewer LJ. Precision agriculture in China: exploring awareness, understanding, attitudes and perceptions of agricultural experts and end-users in China. Advances in Animal Biosciences. 2017 Jul;8(2):703-7.

[6] Kashiha MA, Bahr C, Ott S, Moons CP, Niewold TA, Tuyttens F, Berckmans D. Automatic monitoring of pig locomotion using image analysis. Livestock Science. 2014 Jan 1;159:141-8.

[7] Zhu Q, Ren J, Barclay D, McCormack S, Thomson W. Automatic animal detection from kinect sensed images for livestock monitoring and assessment. In2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing 2015 Oct 26 (pp. 1154-1157). IEEE.

[8] Vranken E, Berckmans D. Precision livestock farming for pigs. Animal Frontiers. 2017 Jan 1;7(1):32-7.

[9] Benjamin M, Yik S. Precision livestock farming in swine welfare: a review for swine practitioners. Animals. 2019 Apr;9(4):133.

[10] Artmann R. Electronic identification systems: state of the art and their further development. Computers and electronics in agriculture. 1999 Nov 1;24(1-2):5-26.

[11] The Pig Cough Monitor (PCM), Sound Analysis For Automatic Health Monitoring https://www.fancom.com/uploads/files/a/6/a630b18f680eb7126ce067708d068611ab2f8627.pdf

[12] Sellier N, Guettier E, Staub C. A review of methods to measure animal body temperature in precision farming.

[13] Soerensen DD, Pedersen LJ. Infrared skin temperature measurements for monitoring health in pigs: a review. Acta veterinaria scandinavica. 2015 Dec 1;57(1):5.

[14] Terrasson G, Llaria A, Marra A, Voaden S. Accelerometer based solution for precision livestock farming: geolocation enhancement and animal activity identification. InIOP Conference Series: Materials Science and Engineering 2016 Jul (Vol. 138, No. 1, p. 012004). IOP Publishing.

[15] Watanabe N, Sakanoue S, Kawamura K, Kozakai T. Development of an automatic classification system for eating, ruminating and resting behavior of cattle using an accelerometer. Grassland science. 2008 Dec;54(4):231-7.

[16] Caja G, Conill C, Nehring R, Ribó O. Development of a ceramic bolus for the permanent electronic identification of sheep, goat and cattle. Computers and electronics in agriculture. 1999 Nov 1;24(1-2):45-63.

[17] Garín D, Caja G, Bocquier F. Effects of small ruminal boluses used for electronic identification of lambs on the growth and development of the reticulorumen. Journal of animal science. 2003 Apr 1;81(4):879-84.

[18] Caja G, Hernández-Jover M, Conill C, Garín D, Alabern X, Farriol B, Ghirardi J. Use of ear tags and injectable transponders for the identification and traceability of pigs from birth to the end of the slaughter line. Journal of animal science. 2005 Sep 1;83(9):2215-24.

[19] Voulodimos AS, Patrikakis CZ, Sideridis AB, Ntafis VA, Xylouri EM. A complete farm management system based on animal identification using RFID technology. Computers and electronics in agriculture. 2010 Mar 1;70(2):380-8.

[20] Adrion F, Kapun A, Holland EM, Staiger M, Löb P, Gallmann E. Novel approach to determine the influence of pig and cattle ears on the performance of passive UHF-RFID ear tags. Computers and Electronics in Agriculture. 2017 Aug 1;140:168-79.

[21] Wada, N.; Shinya, M.; Shiraishi, M. [Short Paper] Pig Face Recognition Using Eigenspace Method. ITE Trans. Media Technol. Appl. 2013, 1, 328–332. doi:10.3169/mta.1.328.

[22] Hansen MF, Smith ML, Smith LN, Salter MG, Baxter EM, Farish M, Grieve B. Towards on-farm pig face recognition using convolutional neural networks. Computers in Industry. 2018 Jun 1;98:145-52.

[23] Tscharke M, Banhazi TM. A brief review of the application of machine vision in livestock behaviour analysis. Agrárinformatika/Journal of Agricultural Informatics. 2016;7(1):23-42.

[24] Lind NM, Vinther M, Hemmingsen RP, Hansen AK. Validation of a digital video tracking system for recording pig locomotor behaviour. Journal of neuroscience methods. 2005 Apr 30;143(2):123-32.

[25] Jeong S, Jeong H, Kim H, Yoe H. Cloud computing based livestock monitoring and disease forecasting system. International Journal of Smart Home. 2013;7(6):313-20.

[26] Santos-González I, Rivero-García A, González-Barroso T, Molina-Gil J, Caballero-Gil P. Real-Time Streaming: A Comparative Study Between RTSP and WebRTC. InUbiquitous Computing and Ambient Intelligence 2016 Nov 29 (pp. 313-325). Springer, Cham.

[27] Nasirahmadi A, Edwards SA, Sturm B. Implementation of machine vision for detecting behaviour of cattle and pigs. Livestock Science. 2017 Aug 1;202:25-38.

[28] Ahrendt P, Gregersen T, Karstoft H. Development of a real-time computer vision system for tracking loose-housed pigs. Computers and Electronics in Agriculture. 2011 May 1;76(2):169-74.

[29] Anglart, D., 2016. Automatic Estimation of Body Weight and Body Condition Score in Dairy Cows Using 3D imaging technique. Second cycle A2E SLU, Dept. of Animal Nutrition and Management, Uppsala.

[30] Azzaro G, Caccamo M, Ferguson JD, Battiato S, Farinella GM, Guarnera GC, Puglisi G, Petriglieri R, Licitra G. Objective estimation of body condition score by modeling cow body shape from digital images. Journal of dairy science. 2011 Apr 1;94(4):2126-37.

[31] Bercovich A, Edan Y, Alchanatis V, Moallem U, Parmet Y, Honig H, Maltz E, Antler A, Halachmi I. Development of an automatic cow body condition scoring using body shape signature and Fourier descriptors. Journal of dairy science. 2013 Dec 1;96(12):8047-59.

[32] Bewley JM, Peacock AM, Lewis O, Boyce RE, Roberts DJ, Coffey MP, Kenyon SJ, Schutz MM. Potential for estimation of body condition scores in dairy cattle from digital images. Journal of dairy science. 2008 Sep 1;91(9):3439-53.

[33] Brandl N, Jørgensen E. Determination of live weight of pigs from dimensions measured using image analysis. Computers and electronics in agriculture. 1996 May 1;15(1):57-72.

[34] Cangar Ö, Leroy T, Guarino M, Vranken E, Fallon R, Lenehan J, Mee J, Berckmans D. Automatic real-time monitoring of locomotion and posture behaviour of pregnant cows prior to calving using online image analysis. Computers and electronics in agriculture. 2008 Nov 1;64(1):53-60.

[35] Colak A, Polat B, Okumus Z, Kaya M, Yanmaz LE, Hayirli A. Early Detection of Mastitis Using Infrared Thermography in Dairy Cows1. Journal of Dairy Science. 2008 Nov 1;91(11):4244-8.

[36] Cortivo PD, Dias E, Barcellos JO, Peripolli V, Costa Jr JB, Dallago BS, McManus CM. Use of thermographic images to detect external parasite load in cattle. Computers and Electronics in Agriculture. 2016 Sep 1;127:413-7.

[37] Costa A, Ismayilova G, Borgonovo F, Viazzi S, Berckmans D, Guarino M. Image-processing technique to measure pig activity in response to climatic variation in a pig barn. Animal Production Science. 2014 Jul 14;54(8):1075-83.

[38] Doeschl-Wilson AB, Whittemore CT, Knap PW, Schofield CP. Using visual image analysis to describe pig growth in terms of size and shape. Animal science. 2004 Dec;79(3):415-27.

[39] Fischer A, Luginbühl T, Delattre L, Delouard JM, Faverdin P. Rear shape in 3 dimensions summarized by principal component analysis is a good predictor of body condition score in Holstein dairy cows. Journal of dairy science. 2015 Jul 1;98(7):4465-76.

[40] Frost AR, Tillett RD, Welch SK. The development and evaluation of image analysis procedures for guiding a livestock monitoring sensor placement robot. Computers and Electronics in Agriculture. 2000 Sep 1;28(3):229-42.

[41] Gloster J, Ebert K, Gubbins S, Bashiruddin J, Paton DJ. Normal variation in thermal radiated temperature in cattle: implications for foot-and-mouth disease detection. BMC veterinary research. 2011 Dec;7(1):73.

[42] González-Velasco HM, García-Orellana CJ, Macías-Macías M, Gallardo-Caballero R, García-Manso A. A morphological assessment system for 'show quality'bovine livestock based on image analysis. Computers and electronics in agriculture. 2011 Aug 1;78(1):80-7.

[43] Gronskyte R, Clemmensen LH, Hviid MS, Kulahci M. Monitoring pig movement at the slaughterhouse using optical flow and modified angular histograms. Biosystems Engineering. 2016 Jan 1;141:19-30.

[44] Gronskyte R, Clemmensen LH, Hviid MS, Kulahci M. Pig herd monitoring and undesirable tripping and stepping prevention. Computers and Electronics in Agriculture. 2015 Nov 1;119:51-60.

[45] Guo YZ, Zhu WX, Jiao PP, Ma CH, Yang JJ. Multi-object extraction from topview group-housed pig images based on adaptive partitioning and multilevel thresholding segmentation. Biosystems Engineering. 2015 Jul 1;135:54-60.

[46] Guzhva O, Ardö H, Herlin A, Nilsson M, Åström K, Bergsten C. Feasibility study for the implementation of an automatic system for the detection of social interactions in the waiting area of automatic milking stations by using a video surveillance system. Computers and Electronics in Agriculture. 2016 Sep 1;127:506-9.

[47] Halachmi I, Klopčič M, Polak P, Roberts DJ, Bewley JM. Automatic assessment of dairy cattle body condition score using thermal imaging. Computers and electronics in agriculture. 2013 Nov 1;99:35-40.

[48] Halachmi I, Polak P, Roberts DJ, Klopcic M. Cow body shape and automation of condition scoring. Journal of dairy science. 2008 Nov 1;91(11):4444-51.

[49] Hoffmann G, Schmidt M, Ammon C, Rose-Meierhöfer S, Burfeind O, Heuwieser W, Berg W. Monitoring the body temperature of cows and calves using video recordings from an infrared thermography camera. Veterinary research communications. 2013 Jun 1;37(2):91-9.

[50] Hovinen M, Siivonen J, Taponen S, Hänninen L, Pastell M, Aisla AM, Pyörälä S. Detection of clinical mastitis with the help of a thermal camera. Journal of Dairy Science. 2008 Dec 1;91(12):4592-8.

[51] Jabbar KA, Hansen MF, Smith ML, Smith LN. Early and non-intrusive lameness detection in dairy cows using 3-dimensional video. Biosystems Engineering. 2017 Jan 1;153:63-9.

[52] Jover JN, Alcaniz-Raya M, Gomez V, Balasch S, Moreno JR, Colomer VG, Torres A. An automatic colour-based computer vision algorithm for tracking the position of piglets. Spanish Journal of Agricultural Research. 2009 Sep 1;7(3):535-49.

[53] Kashiha M, Bahr C, Haredasht SA, Ott S, Moons CP, Niewold TA, Ödberg FO, Berckmans D. The automatic monitoring of pigs water use by cameras. Computers and Electronics in Agriculture. 2013 Jan 1;90:164-9.

[54] Kashiha M, Bahr C, Ott S, Moons CP, Niewold TA, Ödberg FO, Berckmans D. Automatic identification of marked pigs in a pen using image pattern recognition. Computers and electronics in agriculture. 2013 Apr 1;93:111-20.

[55] Kashiha M, Bahr C, Ott S, Moons CP, Niewold TA, Ödberg FO, Berckmans D. Automatic weight estimation of individual pigs using image analysis. Computers and Electronics in Agriculture. 2014 Sep 1;107:38-44.

[56] Kashiha MA, Bahr C, Ott S, Moons CP, Niewold TA, Tuyttens F, Berckmans D. Automatic monitoring of pig locomotion using image analysis. Livestock Science. 2014 Jan 1;159:141-8.

[57] Kongsro J. Development of a computer vision system to monitor pig locomotion. Open Journal of Animal Sciences. 2013 Jul 1;3(3):254.

[58] Kongsro J. Estimation of pig weight using a Microsoft Kinect prototype imaging system. Computers and electronics in agriculture. 2014 Nov 1;109:32-5.

[59] Kuzuhara Y, Kawamura K, Yoshitoshi R, Tamaki T, Sugai S, Ikegami M, Kurokawa Y, Obitsu T, Okita M, Sugino T, Yasuda T. A preliminarily study for predicting body weight and milk properties in lactating Holstein cows using a three-dimensional camera system. Computers and Electronics in Agriculture. 2015 Feb 1;111:186-93.

[60] Lao F, Brown-Brandl T, Stinn JP, Liu K, Teng G, Xin H. Automatic recognition of lactating sow behaviors through depth image processing. Computers and Electronics in Agriculture. 2016 Jul 31;125:56-62.

[61] Lee J, Jin L, Park D, Chung Y. Automatic recognition of aggressive behavior in pigs using a kinect depth sensor. Sensors. 2016 May 2;16(5):631.

[62] Liu B, Zhu W. Segmentation improvement of pig contour based on registration and fusion of IR thermal and optical images. InNatural Computation (ICNC), 2013 Ninth International Conference on 2013 Jul 23 (pp. 1424-1428). IEEE.

[63] McFarlane NJ, Schofield CP. Segmentation and tracking of piglets in images. Machine vision and applications. 1995 May 1;8(3):187-93.

[64] Montanholi YR, Odongo NE, Swanson KC, Schenkel FS, McBride BW, Miller SP. Application of infrared thermography as an indicator of heat and methane production and its use in the study of skin temperature in response to physiological events in dairy cattle (Bos taurus). Journal of Thermal Biology. 2008 Dec 1;33(8):468-75.

[65] Nasirahmadi A, Edwards SA, Sturm B. Investigating the effect of rooting substrate provision on the group lying behaviour of pigs using machine vision. InCIGR-AgEng Conference 2016 2016. Newcastle University.

[66] Nasirahmadi A, Hensel O, Edwards SA, Sturm B. A new approach for categorizing pig lying behaviour based on a Delaunay triangulation method. animal. 2017 Jan;11(1):131-9.

[67] Nasirahmadi A, Hensel O, Edwards SA, Sturm B. Automatic detection of mounting behaviours among pigs using image analysis. Computers and Electronics in Agriculture. 2016 Jun 1;124:295-302.

[68] Nasirahmadi A, Richter U, Hensel O, Edwards S, Sturm B. Using machine vision for investigation of changes in pig group lying patterns. Computers and Electronics in Agriculture. 2015 Nov 1;119:184-90.

[69] Nilsson M, Herlin AH, Ardö H, Guzhva O, Åström K, Bergsten C. Development of automatic surveillance of animal behaviour and welfare using image analysis and machine learned segmentation technique. Animal. 2015 Nov;9(11):1859-65.

[70] Oczak M, Viazzi S, Ismayilova G, Sonoda LT, Roulston N, Fels M, Bahr C, Hartung J, Guarino M, Berckmans D, Vranken E. Classification of aggressive behaviour in pigs by activity index and multilayer feed forward neural network. Biosystems Engineering. 2014 Mar 1;119:89-97.

[71] Ott S, Moons CP, Kashiha MA, Bahr C, Tuyttens FA, Berckmans D, Niewold TA. Automated video analysis of pig activity at pen level highly correlates to human observations of behavioural activities. Livestock Science. 2014 Feb 1;160:132-7.

[72] Ozkaya S. The prediction of live weight from body measurements on female Holstein calves by digital image analysis. The Journal of Agricultural Science. 2013 Aug;151(4):570-6.

[73] Pluk A, Bahr C, Poursaberi A, Maertens W, Van Nuffel A, Berckmans D. Automatic measurement of touch and release angles of the fetlock joint for lameness detection in dairy cattle using vision techniques. Journal of dairy Science. 2012 Apr 1;95(4):1738-48.

[74] Porto SM, Arcidiacono C, Anguzza U, Cascone G. A computer vision-based system for the automatic detection of lying behaviour of dairy cows in free-stall barns. Biosystems Engineering. 2013 Jun 1;115(2):184-94.

[75] Porto SM, Arcidiacono C, Anguzza U, Cascone G. The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision-based system. Biosystems Engineering. 2015 May 1;133:46-55.

[76] Porto SM, Arcidiacono C, Guarnera GC, Cascone G. Preliminary study for the implementation ofan image analysis algorithm to detect dairy cow presence at the feed barrier. Journal of Agricultural Engineering. 2012 Jun 22;42(4):17-24.

[77] Poursaberi A, Bahr C, Pluk A, Van Nuffel A, Berckmans D. Real-time automatic lameness detection based on back posture extraction in dairy cattle: Shape analysis of cow with image processing techniques. Computers and Electronics in Agriculture. 2010 Oct 1;74(1):110-9.

[78] Rainwater-Lovett K, Pacheco JM, Packer C, Rodriguez LL. Detection of foot-and-mouth disease virus infected cattle using infrared thermography. The Veterinary Journal. 2009 Jun 1;180(3):317-24.

[79] Salau J, Haas JH, Junge W, Bauer U, Harms J, Bieletzki S. Feasibility of automated body trait determination using the SR4K time-of-flight camera in cow barns. SpringerPlus. 2014 Dec 1;3(1):225.

[80] Schaefer AL, Cook N, Tessaro SV, Deregt D, Desroches G, Dubeski PL, Tong AK, Godson DL. Early detection and prediction of infection using infrared thermography. Canadian journal of animal science. 2004 Mar 1;84(1):73-80.

[81] Schofield CP, Marchant JA, White RP, Brandl N, Wilson M. Monitoring pig growth using a prototype imaging system. Journal of Agricultural Engineering Research. 1999 Mar 1;72(3):205-10.

[82] Schofield CP. Evaluation of image analysis as a means of estimating the weight of pigs. Journal of Agricultural Engineering Research. 1990 Sep 1;47:287-96.

[83] Shao B, Xin H. A real-time computer vision assessment and control of thermal comfort for group-housed pigs. Computers and electronics in agriculture. 2008 Jun 1;62(1):15-21.

[84] Shao J, Xin H, Harmon JD. Comparison of image feature extraction for classification of swine thermal comfort behavior1. Computers and electronics in agriculture. 1998 Mar 1;19(3):223-32.

[85] Shelley AN. Monitoring Dairy Cow Feed Intake Using Machine Vision.

[86] Shi C, Teng G, Li Z. An approach of pig weight estimation using binocular stereo system based on LabVIEW. Computers and Electronics in Agriculture. 2016 Nov 1;129:37-43.

[87] Spoliansky R, Edan Y, Parmet Y, Halachmi I. Development of automatic body condition scoring using a low-cost 3-dimensional Kinect camera. Journal of dairy science. 2016 Sep 1;99(9):7714-25.

[88] Stajnko, D., Brus, M., Hočevar, M., 2008. Estimation of bull live weight through thermographically measured body dimensions. Comput. Electron. Agric. 61 (2), 233–240.

[89] Stavrakakis S, Guy JH, Syranidis I, Johnson GR, Edwards SA. Pre-clinical and clinical walking kinematics in female breeding pigs with lameness: A nested case-control cohort study. The Veterinary Journal. 2015 Jul 1;205(1):38-43.

[90] Stavrakakis S, Li W, Guy JH, Morgan G, Ushaw G, Johnson GR, Edwards SA. Validity of the Microsoft Kinect sensor for assessment of normal walking patterns in pigs. Computers and Electronics in Agriculture. 2015 Sep 1;117:1-7.

[91] TAŞDEMİR Ş, ÜRKMEZ A, İNAL Ş. A fuzzy rule-based system for predicting the live weight of Holstein cows whose body dimensions were determined by image analysis. Turkish Journal of Electrical Engineering & Computer Sciences. 2011 Jun 1;19(4):689-703.

[92] Tasdemir S, Urkmez A, Inal S. Determination of body measurements on the Holstein cows using digital image analysis and estimation of live weight with regression analysis. Computers and Electronics in Agriculture. 2011 May 1;76(2):189-97.

[93] Tillett RD, Onyango CM, Marchant JA. Using model-based image processing to track animal movements. Computers and electronics in agriculture. 1997 May 1;17(2):249-61.

[94] Tsai DM, Huang CY. A motion and image analysis method for automatic detection of estrus and mating behavior in cattle. Computers and electronics in agriculture. 2014 Jun 1;104:25-31.

[95] Van Hertem T, Alchanatis V, Antler A, Maltz E, Halachmi I, Schlageter-Tello A, Lokhorst C, Viazzi S, Romanini CE, Pluk A, Bahr C. Comparison of segmentation algorithms for cow contour extraction from natural barn background in side view images. Computers and electronics in agriculture. 2013 Feb 1;91:65-74.

[96] Viazzi S, Bahr C, Schlageter-Tello A, Van Hertem T, Romanini CE, Pluk A, Halachmi I, Lokhorst C, Berckmans D. Analysis of individual classification of lameness using automatic measurement of back posture in dairy cattle. Journal of Dairy Science. 2013 Jan 1;96(1):257-66.

[97] Viazzi S, Bahr C, Van Hertem T, Schlageter-Tello A, Romanini CE, Halachmi I, Lokhorst C, Berckmans D. Comparison of a three-dimensional and two-dimensional camera system for automated measurement of back posture in dairy cows. Computers and Electronics in Agriculture. 2014 Jan 1;100:139-47.

[98] Viazzi S, Ismayilova G, Oczak M, Sonoda LT, Fels M, Guarino M, Vranken E, Hartung J, Bahr C, Berckmans D. Image feature extraction for classification of aggressive interactions among pigs. Computers and Electronics in Agriculture. 2014 Jun 1;104:57-62.

[99] Wang Y, Yang W, Winter P, Walker L. Walk-through weighing of pigs using machine vision and an artificial neural network. Biosystems Engineering. 2008 May 1;100(1):117-25.

[100] Weber A, Salau J, Haas JH, Junge W, Bauer U, Harms J, Suhr O, Schönrock K, Rothfuß H, Bieletzki S, Thaller G. Estimation of backfat thickness using extracted traits from an automatic 3D optical system in lactating Holstein-Friesian cows. Livestock Science. 2014 Jul 1;165:129-37.

[101] Wirthgen T, Zipser S, Franze U, Geidel S, Lempe G. Automatic infrared based temperature measuring system for health monitoring in veterinary applications. InSensors, 2011 IEEE 2011 Oct 28 (pp. 1800-1803). IEEE.

[102] Wongsriworaphon A, Arnonkijpanich B, Pathumnakul S. An approach based on digital image analysis to estimate the live weights of pigs in farm environments. Computers and Electronics in Agriculture. 2015 Jul 1;115:26-33.

[103] Wu J, Tillett R, McFarlane N, Ju X, Siebert JP, Schofield P. Extracting the three-dimensional shape of live pigs using stereo photogrammetry. Computers and Electronics in Agriculture. 2004 Sep 1;44(3):203-22.

[104] Zhu W, Pu X, Li X, Zhu X. Automated detection of sick pigs based on machine vision. InIntelligent Computing and Intelligent Systems, 2009. ICIS 2009. IEEE International Conference on 2009 Nov 20 (Vol. 2, pp. 790-794). IEEE.

[105] Song X, Leroy T, Vranken E, Maertens W, Sonck B, Berckmans D. Automatic detection of lameness in dairy cattle—Vision-based trackway analysis in cow's locomotion. Computers and electronics in agriculture. 2008 Nov 1;64(1):39-44.

[106] Ashton K. That ‘internet of things’ thing. RFID journal. 2009 Jul 22;22(7):97-114.

[107] Ryu M, Yun J, Miao T, Ahn IY, Choi SC, Kim J. Design and implementation of a connected farm for smart farming system. InSENSORS, 2015 IEEE 2015 Nov 1 (pp. 1-4). IEEE.

[108] Moeslund TB, Granum E. A survey of computer vision-based human motion capture. Computer vision and image understanding. 2001 Mar 1;81(3):231-68.

[109] Oczak M, Ismayilova G, Costa A, Viazzi S, Sonoda LT, Fels M, Bahr C, Hartung J, Guarino M, Berckmans D, Vranken E. Analysis of aggressive behaviours of pigs by automatic video recordings. Computers and electronics in agriculture. 2013 Nov 1;99:209-17.

[110] Begen A, Akgul T, Baugher M. Watching video over the web: Part 1: Streaming protocols. IEEE Internet Computing. 2010 Dec 30;15(2):54-63.

[111] Santos-González I, Rivero-García A, González-Barroso T, Molina-Gil J, Caballero-Gil P. Real-Time Streaming: A Comparative Study Between RTSP and WebRTC. InUbiquitous Computing and Ambient Intelligence 2016 Nov 29 (pp. 313-325). Springer, Cham.

[112] Bapayya K, Sujitha K, Basha A. RTSP Based Video Surveillance System Using IP Camera for Human Detection in OpenCV. International Journal of Computer Science and Software Engineering (IJCSSE). 2015;4(9):243-7.

[113] Ji Q, Yu H, Chen H. A smart Android based remote monitoring system. In2015 Third International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAEECE) 2015 Apr 29 (pp. 181-184). IEEE.

[114] FFmpeg: Official web page. https://www.ffmpeg.org/

[115] Bellas N, Chai SM, Dwyer M, Linzmeier D. Real-time fisheye lens distortion correction using automatically generated streaming accelerators. In2009 17th IEEE Symposium on Field Programmable Custom Computing Machines 2009 Apr 5 (pp. 149-156). IEEE.

[116] Lubbers P. Html5 web sockets: A quantum leap in scalability for the web. http://www. websocket. org/quantum. html. 2011.

[117] Pimentel V, Nickerson BG. Communicating and displaying real-time data with websocket. IEEE Internet Computing. 2012 Jul;16(4):45-53.

[118] Mittek M, Psota ET, Pérez LC, Schmidt T, Mote B. Health monitoring of group-housed pigs using depth-enabled multi-object tracking. InProceedings of Int Conf Pattern Recognit, Workshop on Visual observation and analysis of Vertebrate And Insect Behavior 2016 Feb.

[119] Ron Ketchem and Mark Rix, Swine Management Services LLC, Fremont What does 784,000 services on high producing farms say? Jul 03, 2016

[120] Simina Mistreanu China's Swine Fever Crisis Will Impact Global Trade Well Into 2020. https://www.forbes.com/sites/siminamistreanu/2019/12/28/chinas-swine-fever-crisis-will-impact-global-trade-well-into-2020/#33fb4e31ae04

[121] D'Eath RB, Jack M, Futro A, Talbot D, Zhu Q, Barclay D, Baxter EM. Automatic early warning of tail biting in pigs: 3D cameras can detect lowered tail posture before an outbreak. PloS one. 2018;13(4).

[122] Prewitt JM, Mendelsohn ML. The analysis of cell images. Annals of the New York Academy of Sciences. 1966 Jan;128(3):1035-53.

[123] Otsu N. A threshold selection method from gray-level histograms. IEEE transactions on systems, man, and cybernetics. 1979 Jan;9(1):62-6.

[124] Rosin PL. Measuring shape: ellipticity, rectangularity, and triangularity. Machine Vision and Applications. 2003 Jul 1;14(3):172-84.

[125] Prokop RJ, Reeves AP. A survey of moment-based techniques for unoccluded object representation and recognition. CVGIP: Graphical Models and Image Processing. 1992 Sep 1;54(5):438-60.

[126] Chui CK, Chen G. Kalman filtering. Springer International Publishing; 2017.

[127] Alpha beta filter: https://en.wikipedia.org/wiki/Alpha_beta_filter

[128] Alpha beta filter C source code: http://adrianboeing.blogspot.com/2010/03/alpha-beta-filters.html

[129] Kim J, Choi Y, Ju M, Sa J, Chung Y, Park D, Kim H. Lying-pig detection using depth information. InProceedings of the International Conference on Algorithms, Computing and Systems 2017 Aug 10 (pp. 40-43).

[130] Han Y, Ren J, Zhu Q, Barclay D, Windmill J. IoT and Cloud Enabled Evidence-Based Smart Decision-Making Platform for Precision Livestock Farming. InInternational Conference on Brain Inspired Cognitive Systems 2019 Jul 13 (pp. 570-582). Springer, Cham.

[131] Protecting Computers Against Dust in Industrial and Warehouse Environments. https://www.dbk.com/pdf/DAP_Whitepaper_-_Protecting_Computers_Against_Dust.pdf

Appendix A

Summary of cattle monitoring system

Monitoring	Imaging system	Technique	Source
Live weight	2D (CCD camera)	Based on hip height, body length, hip width, and chest depth.	[72][91][92]
	2D (Thermal camera)	Based on the tail root and front hoof templates.	[88]
	3D (TOF sensor)	Based on 3D and contour features of the body.	[29]
Body shape and condition	2D (CCD camera)	Based on anatomical points (points around hook and tail).	[30][32]
	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.	[31]
	2D (CCD camera)	Based on RGB and body features.	[42][95]
	2D (Thermal camera)	Based on the thickness of fat and muscle layers.	[47][48]
	3D (TOF and depth imaging sensors)	Based on body features and back postures.	[39][59][79][87][100]
Health and disease	2D (Thermal camera)	Based on udder surface temperature.	[35][41][49][50][64][78][80][101]
	2D (Thermal camera)	Based on body surface temperature.	[36]
Feeding and drinking behaviour	2D (Thermal camera)	Based on the Viola-Jones algorithm.	[75][76]
	3D (Structured light illumination scanning)	Based on the change in the volume of food.	[85]
Lying behaviour	2D (CCD camera)	Based on the x–y coordinates of the geometric centre of the animal.	[34]
		Based on the Viola and Jones algorithm.	[74]
Locomotion and lameness behaviour	2D (CCD camera)	Based on body features extraction from a binary image.	[105]
		Based on the touch and release angles in the fetlock joint of the leg along with pressure mat data.	[73]
		Based on the curvature of the back of each animal.	[77][96]
	3D (Kinect sensor)	Based on 3D and 2D features of depth and binary images.	[97]
	3D (Depth video)	Based on tracking hooks and spine of animal in depth image.	[51]
Aggressive behaviour	2D (CCD camera)	Based on geometric features between animals.	[46]
Mounting behaviour	2D (CCD camera)	Based on motion detection and length of moving animals.	[94]

Table 10 Summary image processing methods used for cattle monitoring.

Summary of pig monitoring system

Monitoring	Imaging system	Technique	Source
Live weight	2D (CCD camera)	Based on length and width dimension and boundary area.	[33][38][81][82]
		Based on the area, convex area, perimeter, eccentricity, major and minor axis length.	[55][99][102]
	3D (Kinect sensor)	Based on volume and area of the body.	[58]
	3D (Stereo Vision)	Based on body length, withers height and back area.	[86]
Body shape and condition	2D (Thermal camera)	Based on shape and contour detection.	[62]
	3D (Stereo photogrammetry)	Based on triangulating on animal natural skin texture.	[103]
Health and disease	2D (CCD camera)	Based on daily movement pattern in binary images.	[104]
Tracking	2D (CCD camera)	Based on blob edge and an ellipse fitting technique.	[54][63]
		Based on x-y coordinates of shape.	[93]
		Based on positions of locatable features (kinks) of the body.	[40]
		Based on RGB values.	[52]
		Based on building up support maps and Gaussian model.	[28]
		Learning-based segmentation	[69]
		Based on adaptive partitioning and multilevel thresholding segmentation.	[45]
Feeding and drinking behaviour	2D (CCD camera)	Based on fitted ellipse features and distance to drinking nipple.	[53]
	3D (Kinect sensor)	Based on depth image and x-y coordinates of binary image	[60]
Lying behaviour	2D (CCD camera)	Based on features of the binary image.	[83][84]
		Based on the pixel intensity in the binary image.	[37]
		Based on the fitted ellipse and the DT features.	[65][66][68]
Locomotion and lameness behaviour	2D (CCD camera)	Based on RGB and image map values.	[57]
		Based on the activity index.	[71]
		Based on fitted ellipse features in consecutive frames.	[56][68]
		Based on the optical flow pattern.	[43][44]
	3D (Kinect sensor)	Based on Vicon 3D optoelectronic motion analysis.	[89][90]
Aggressive behaviour	2D (CCD camera)	Based on the motion history image and activity index.	[70][98]
	3D (Kinect sensor)	Based on features from the depth image.	[61]
Mounting behaviour	2D (CCD camera)	Based on fitted ellipse features and ED between animals.	[67]

Table 11 Summary image processing methods used for pig monitoring.

Appendix B

C code for alpha-beta filter

```c
#include <stdio.h>
#include <stdlib.h>
#include <math.h>


typedef struct {
	float alpha; //alpha value (effects x, eg pos)
	float beta; //beta value (effects v, eg vel)
	float xk_1; //current x-estimate
	float vk_1; //current v-estimate
} AlphaBeta;

void InitializeAlphaBeta(float x_measured, float alpha, float beta, AlphaBeta* pab)
{
	pab->xk_1 = x_measured;
	pab->vk_1 = 0;
	pab->alpha = alpha;
	pab->beta = beta;
}


void AlphaBetaFilter(float x_measured, float dt, AlphaBeta* pab)
{
	float xk_1 = pab->xk_1;
	float vk_1 = pab->vk_1;
	float alpha = pab->alpha;
	float beta = pab->beta;

	float xk; //current system state (ie: position)
	float vk; //derivative of system state (ie: velocity)
	float rk; //residual error

	//update our (estimated) state 'x' from the system
	xk = xk_1 + dt * vk_1;
	//update (estimated) velocity
	vk = vk_1;
	//what is our residual error (mesured - estimated)
	rk = x_measured - xk;
	//update our estimates given the residual error.
	xk = xk + alpha * rk;
	vk = vk + beta / dt * rk;
	//finished!

	//now all our "currents" become our "olds" for next time
	pab->vk_1 = vk;
	pab->xk_1 = xk;
}

double frand()
{
	return 2 * ((rand() / (double)RAND_MAX) - 0.5);
}
```

```
int main(int argc, char *argv[])
{
	AlphaBeta ab_x;
	AlphaBeta ab_y;
	double t; //time
	double x, y; //ideal x-y coordinates
	double xm, ym; //measured x-y coordinates
	double xnoise = 0; //noise we are inserting into our system
	double ynoise = 0;
	double m_error = 0; //total error (measured vs ideal)
	double ab_error = 0; //total error (ab filter vs ideal)
#define DT 0.1
	//intialize the AB filters
	InitializeAlphaBeta(1, 0.85, 0.001, &ab_x); //x position
	InitializeAlphaBeta(0, 1.27, 0.009, &ab_y); //y position
	srand(0);

	for (t = 0; t < 4; t += DT)
	{
		//our 'true' position (A circle)
		x = cos(t);
		y = sin(t);
		//update our simulated noise & drift
		xnoise += frand()*0.01;
		ynoise += frand()*0.01;
		//our 'measured' position (has some noise)
		xm = x + xnoise;
		ym = y + ynoise;
		//our 'filtered' position (removes some noise)
		AlphaBetaFilter(xm, DT, &ab_x);
		AlphaBetaFilter(ym, DT, &ab_y);

		//update error sum (for statistics only)
		m_error += fabs(x - xm) + fabs(y - ym);
		ab_error += fabs(x - ab_x.xk_1) + fabs(y - ab_y.xk_1);
	}
	return 0;
}
```

Appendix C

List of author's publications

1. **Yukang Han**, Jinchang Ren, Qiming Zhu, David Barclay, James Windmill. IoT and Cloud Enabled Evidence-Based Smart Decision-Making Platform for Precision Livestock Farming. 10th International Conference, BICS 2019, Guangzhou, China, July 13–14, 2019, Proceedings.

2. Mingchen Feng, Jiangbin Zheng, **Yukang Han**, Jinchang Ren, Qiaoyuan Liu. Big Data Analytics and Mining for Crime Data Analysis, Visualization and Prediction. BICS 2018: Advances in Brain Inspired Cognitive Systems.