DEVELOPING REMOTE MONITORING METHODS FOR EARLY DETECTION OF RESPIRATORY DISEASE IN PIGS

A1-104

Final Report prepared for the Australasian Pork Research Institute Limited (APRIL)

By

Ellen Jongman, Maria Jorquera-Chavez, Frank Dunshea, Sigfredo Fuentes, Tomas Poblete, Ranjith Rajasekhara, Rebecca Morisson

Contact author: EJongman@unimelb.edu.au
Animal Welfare Science Centre
Faculty of Veterinary and Agricultural Sciences
University of Melbourne<Authors>

April 2020

Australasian Pork Research Institute Ltd
APRIL

Executive Summary

Respiratory diseases in pigs causes suffering in infected animals, impacts the pig industry by increasing the cost of production and affects public health by the increased use of antimicrobials and the development of antimicrobial resistance. One of the most appropriate approaches to minimizing these negative effects is the early detection of infected animals. Physiological parameters such as core body temperature, heart rate (HR) and respiration rate (RR), could be useful indicators when monitoring illness in pigs. However, their assessment normally involves procedures that are invasive, labour intensive and consequently not practical for large scale monitoring. The use of cameras together with computer-based technology could assist the early detection of physiological changes in pigs when these are ill. While the use of thermal infrared (TIR) to measure eye temperature has been used more widely, the use of remotely recorded HR and RR in pigs is a novel application.

This pilot study aimed to (a) validate the use of computer-based technology over RGB (red, green, and blue) and thermal infrared imagery to measure HR and RR of pigs, and (b) investigate whether eye-temperature, HR and RR recorded remotely could be used to identify early signs of respiratory diseases in free-moving pigs housed in a commercial piggery. FLIR Duo® Pro R, cameras with a radiometric thermal sensor and a 4K visible RGB sensor, were used in this study to obtain the recordings. Computer algorithms were used to extract eye-temperature and RR from thermal infrared images, and HR from RGB videos.

For the validation of these methods, twenty-eight pigs (9 weeks old) were recorded to remotely assess HR and RR, which were later compared to HR and RR measures obtained with standard methods (stethoscope and visual observations respectively). All correlations between remote and standard methods were positive, ranging between $r = 0.61$ and $r = 0.66$ ($p < 0.05$).

For the investigation of early detection of respiratory disease, a total of 6 mildly sick pigs were identified and compared with 36 healthy pigs (each sick pig paired with six healthy pigs from the same pen). These pigs were recorded by overhead cameras and the remotely-obtained physiological measures were evaluated to identify whether evident changes in these measures could be detected before clinical signs were observed. The changes in eye-temperature and HR remotely obtained showed clear differences between sick and healthy pigs before clinical sigs were detected. However, significant changes of RR occurred only in a later stage of the illness when clinical signs were more apparent.

Although this pilot study had some limitations, such as the low number of pigs that were only mildly affected by respiratory diseases during the analysed period, the results obtained are promising. The results of the present study confirm the utility of computer vision technique to rapidly detect physiological changes related to illness in commercial pigs, and further research is recommended. Further research should be focused toward continuing the development and automatisation of this technology and the further development of algorithms to automatically detect individual pigs under commercial conditions, including physiological changes of animals in different environmental conditions and severity of illness.

Table of Contents

1. Introduction

The detection of health challenges affecting pigs is a relevant factor to maintain appropriate levels of health and animal welfare within commercial piggeries. The early detection of illnesses is crucial to reduce the impact that these have on animals and the industry, and to increase the success of the treatments applied [1]. Pleuropneumonia is one of the diseases that highly impact the pig industry, which easily propagate across pigs between 8 and 16 weeks of age [2]. These diseases are known to deteriorate the wellbeing of pigs and increase the cost of production by the rate of weight loss and death observed in affected pigs, as well as the increase of antibiotics used to prevent and treat these infections [3-7]. Furthermore, the use of antibiotics in animals has become a concern due to antimicrobial resistance (AMR), which has been observed to increase among animals and humans [8,9].

Although the importance of early detection of diseases has been recognised, the implementation of effective detection systems has been limited by the difficulty and high cost of performing large-scale clinical and serological examination [10]. Novel non-invasive methods are being investigated in an attempt to overcome these limitations and help stock people to detect diseases at an early stage and take rapid action, minimising the propagation of the infection within the herd and reducing the use of antibiotics [11]. As part of this attempt, Precision Livestock Farming (PLF) has appeared as one of the most appropriate approaches for constant animal monitoring and early detection of diseases. For instance, non-invasive methods to assess changes in animal behaviour, cough sound and skin temperature are investigated for applications to detect illness in several species [11-13].

In terms of behavioural assessment, automatic systems to detect behavioural changes are in early stages of development [13]. Several studies have attempted to develop partially or fully-automated systems to asses activity, feeding and drinking behaviours, among others. For instance, automatic water meters have been used to measure the drinking behaviour of pigs [14]. Although these sensors were observed to be more accurate than human observers, these sensors do not consider water wastage or individual drinking rate [13,14]. Drinking and feeding behaviour has also been studied by using radio-frequency identification (RFID) transponders attached to pigs and an RFID antenna placed at feeding and drinking areas, which allows the identification of the frequency and duration of visits by individual pigs to the drinker and feeder [13,15,16]. Although these studies have shown promising results measuring drinking and feeding behaviours, further research is needed to improve the accuracy of these methods and the identification of individual pigs when multiple transponders are close to one receiver [13,16]. In addition, activity and laying behaviour has been assessed through imagery and computer-based techniques [17-19].

As mentioned before, non-invasive methods to assess coughing in farm animals has also been reported. For instance, Silva et al. [20] investigated the use of various microphone and a computer algorithm to localise cough attacks, showing a possible use of microphones and computer-based methods for visualizing the spread of respiratory diseases in pigs. Ferrari et al. [11] also indicated the possible use of cough sounds as a warning of developing outbreak of respiratory infections in calves.

Similarly to behavioural changes, physiological changes have been linked to respiratory diseases in animals. Nevertheless, the methods commonly used to measure parameters such as body temperature, heart rate (HR) and respiration rate (RR) require human interaction, and they normally are time-consuming and labour-intensive. For this reason, researchers are also investigating non-invasive techniques to measure the changes in these parameters [10,21-25].

Body temperature is one of the measures that has been extensively used for the detection of sick animals. As part of the search for less invasive and more practical methods, gastric sensors [26,27] and thermal infrared (TIR) cameras [22,28,29] have been studied to detect trends and relevant changes in body temperature of several species. In terms of infrared imagery, Polat et al. [12] showed positive results when using TIR images to detect subclinical mastitis in cows. Schaefer et al. [30] also indicated TIR images to be an useful tool to detect high temperatures related to bovine respiratory disease complex (BRD). Moreover, Cook et al. [31] suggested that TIR images could be used to detect febrile response to vaccination in groups of piglets.

The measurement of HR and RR of animals through the use of imagery and computer-based methods have been less investigated. However, some computer-based methods have been reported to assess HR and RR in humans [32-35]. These studies have used commercial video (red, green and blue; RGB) cameras and TIR cameras to obtain images of people's faces to be processed through computer algorithms and determine their pulse and breathing movements, showing promising results. Although these methods have been less explored in animals, some studies have investigated the possible use of imagery to assess HR [36,37] and RR [25,36,37] in farm animals.

Considering the impact that respiratory disease has on the pig industry in Australia and worldwide, and the challenges related to its detection and treatment, this project investigated the use of TIR cameras and video cameras in a commercial indoor piggery. The aim of this study was to identify whether remote monitoring by video (RGB), thermal infrared images and computer algorithms can be used to detect early signs of respiratory disease in free-moving pigs housed in groups. The result of this project could aid further research and development of this technology as a tool to monitor pigs health and welfare, assisting the improvement of management of pigs on farms.

2. Methodology

2.1. Cameras and image processing

FLIR Duo® Pro R (FLIR Systems, Wilsonville, OR. USA) cameras were used during this project (Figure 1). These combine a high resolution radiometric thermal sensor and a 4K visible RGB sensor. The thermal infrared (TIR) sensor had a spectral range of 7.5 – 13.5 µm, sensitivity < 50 mK, resolution 640 x 512, emissivity of 0.985, and a frame rate of 30 Hz per second. The RGB sensor had a resolution of 4000 x 3000 and a frame rate of 30 Hz per second.

As the second part of this study required continuous monitoring, a storage system was developed using Raspberry Pi (Raspberry Pi Foundation, Cambridge, UK). This storage system was set to record for 15 minutes, then stop the camera to automatically transfer the recordings to an external hard drive (transferring process lasted between 15-20 minutes) and after all the data was transferred to the external hard drive and deleted from the camera the camera recorded for another 15 minutes, and so on.

Collected images were processed using customised algorithms developed in Matlab® R2018b (Mathworks Inc. Natick, MA, USA). In the case of TIR images, this algorithm firstly extracted the radiometric information of each image, by using FLIR® Atlas SDK [36-38]. Secondly, it allowed to select the eye area as the region of interest (ROI; selected on the first frame and automatically tracked over the following frames), from where the maximum temperature was extracted. The selection of eye area as ROIs in this study was based on studies that have shown this area to be more practical and accurate when using TIR images to measure body temperature [22,39].

With the aim of remotely measuring HR over the RGB images, two algorithms were integrated. The first algorithm uses computer vision techniques to recognize spatial patterns on specific ROIs (eye area) and automatically track them along the video [36]. The second algorithm, is based on the photoplethysmography (PPG) principles to assess HR changes by detecting changes on both light reflection off and transmission through body parts [35]. To assess HR in the present study, the eye area was used as ROI because it presents low density hair, and because this area has been shown to be usefulness when using imagery in humans and animals [22,32].

Furthermore, for the analysis of respiration rate TIR images were processed, using the nose area as ROI. Similarly to the HR analysis, the ROI (nose area) is firstly selected and tracked in order to improve the accuracy of the analysis. Subsequently, the algorithm extracts the maximum temperature within the ROI (nose area) in each frame, which are later used to calculate RR. The calculation is based on the changes of temperature that occur due to air flow (inhalation and exhalation), where the air that is expelled generates an increase in temperature within the nose area, decreasing later when the inhalation occurs [36].

Figure 2: FLIR Duo® Pro R cameras. On (a) Front view of camera. On (b) Top view of the camera.

2.2. Animals and sample collection

The facilities and animals used in this project were provided by Rivalea Australia. All animal procedures had prior institutional ethical approval (Protocol ID:17V060C) under the requirement of the New South Wales Prevention of Cruelty to Animals Act (1979) in accordance with the National Health and Medical Research Council/Commonwealth Scientific and Industrial Research Organisation/Australian Animal Commission Australian Code of Practice for the Care and Use of Animals for Scientific Purposes (NHMRC, 2013).

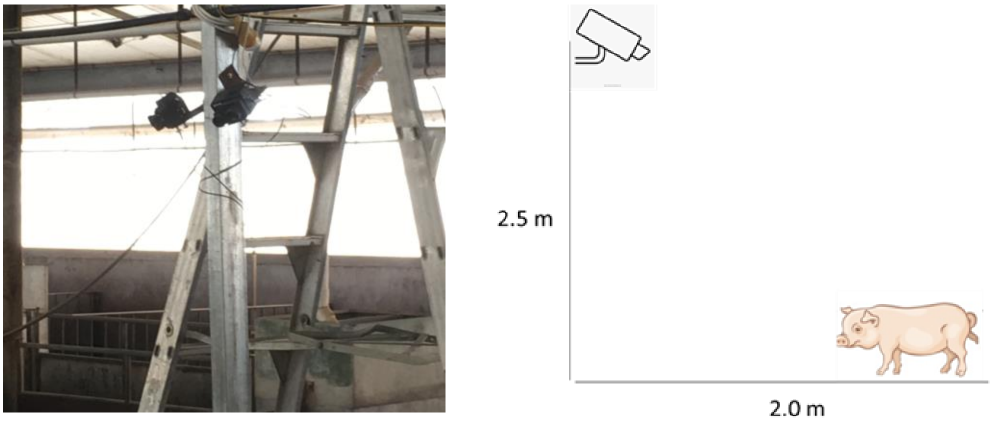
This project had the aim of (i) validating the proposed algorithms to measure HR and RR in pigs and (ii) identify whether these technologies would be able to detect physiological changes (eye-temperature, HR and RR) before sick animals display clinical signs that would be detected by farm workers. Therefore, this project was divided into two parts. “Part one” refers to the study to validate these techniques, while “Part two” refers to the study which implemented these techniques for early detection of respiratory diseases in pigs under commercial conditions.

The data management and analysis were conducted in Microsoft Excel, Minitab® Statistical Software 18 (Minitab Pty Ltd., Sydney, Australia) and Genstat® for Windows 18th Edition (VSN International, Hemel Hempstead, UK).

2.2.1. Part one: Validation study

A total of twenty-eight post-weaned pigs, at 9 weeks of age, were grouped into two adjacent pens (2m x 2.8m). The procedures for this study were performed in November of 2019, four days after these pigs were placed in their respective pens.

A camera (FLIR Duo® Pro R; FLIR Systems, Wilsonville, OR, USA) was located in a corner of each pen, attached at a height of 2.5 m and the camera lenses were directed to record the largest area of the pen possible (Figure 2). An area in the middle of the solid floor (close to the feeder) was selected as the place where pigs were individually held during the recording, which was at approximately 2.5-2.8 metres from the camera.



(a) (b)

Figure 2: Description of camera position. On (a) Image of cameras located at a height of 2.5 metres, each camera directed towards a respective pen. On (b) Diagram of cameras and pigs' position during the validation study.

In order to be able to validate the use of imagery and computer-based techniques to measure HR and RR of pigs in commercial settings, each pig was recorded for a total of two minutes and each parameter was also measured with a gold-standard method during the same period (stethoscope and video-based observations of breathing movements, respectively). Each pig was firstly marked with its respective number using stock spray and then recorded while being held one minute with the face towards the camera, and another minute facing sideways of the camera. During this recording period, a skilled technician measured the HR by using a stethoscope (3M Littmann™ Cardiology II; Littmann™, St. Paul, Minnesota, USA) to hear the number of beats. Due to the challenge of maintaining pigs in the same position for a minute and some pigs vocalising while being held, the technician counted the beats occurring within 30 seconds and repeated this procedure for another consecutive 30-second-period while the pig was toward the camera and two consecutive 30-second-periods while the pig was facing sideways. In addition, the RR was also measured during the same period by counting the breathing movements of the flanks that occurred in one minute. Due to excessive motion and vocalisation, it was not possible to hear the HR of one pig in any position, and in three pig when they were facing towards the camera.

Once the images were processed, the HR and RR obtained remotely were compared to the HR and RR obtained with the standard methods. Pearson correlation and regression analysis were performed to measure the strength of the linear association between remotely measured HR and RR with its respective parameter measured with standard method (stethoscope for HR and visual observations for RR assessment).

2.2.2. Part two: Early detection of respiratory diseases

Two groups of post-weaned pigs were recorded in two separate periods during 2019-2020. The first group comprised 20 pigs, which were divided and placed into two adjoining pens of 2m x 2.8m metres (10 pigs per pen) at 9 weeks of age. These pigs were recorded between 12 and 17 weeks of age (August-September). The second group comprised 28 weaned pigs, which were divided and placed into two adjoining pens of 2m x 2.8m metres (14 pigs per pen) at 9 weeks of age. These pigs were recorded between the 9 and 20 weeks of age (November-January).

One camera, together with a storage system and an external hard drive, was located in each of the pens by attaching it in a corner of the pen at a height of 2.5 m (Figure 2). The location of the camera in the current study was chosen so that additional information on the behaviour of pigs could be collected, which can also potentially be used to identify clinical signs of disease. As the shed was naturally lighted, these cameras were set to stop recording during late night to early morning. Recordings were obtained for 15 minutes, every 30-35 minutes from 5:00 am to 11:00 pm (approximately 30 fifteen-minutes recordings per day). In both groups (both periods of recording), after placing the cameras, each pig was marked with a specific number before the start of the recording. In addition, pigs were re-marked every 7 days.

Pigs were labelled as "sick" or "healthy" based on signs observed (Table 1). The clinical observations were performed daily by farm technicians (as part of their normal routine) and during one hour every 7 days by an external technician who visited the farm, as well as by observing the daily video recordings (performed by the same external technician). When a pig was observed to have two or more symptoms shown in Table 1, it was considered to have a respiratory infection and was labelled as "sick". The animals that did not show any symptoms listed in Table 1 were labelled as "healthy". From a total of six pigs labelled as "sick" during this study, only one of these pigs (referred as 'S6') was detected to be sick by the routine observations performed by stock people at the farm, and the rest of pigs showed very mild symptoms and were only identified as "sick" during close observation of the daily video recordings.

Table 1. Clinical observations used to identify animals with symptoms of respiratory disease.

Symptoms	Observations	Sign of illness
Nasal discharge	None	No
	Discharge for several observations	Yes
Coughing	No coughing	No
	Coughing episodes of 1-3 short coughs at a time	Yes
Laboured breathing	Normal breathing	No
	Abdominal breathing	Yes
	Laboured breathing, breathing through mouth, head extended	Yes
Lethargy	Alert and active	No
	Depressed, disinclination to move about, ears laid back	Yes
	Recumbent position, reluctance to get up	Yes
Anorexia	Eats	No
	Not observed eating	Yes
	Roughness in coat, tucked in and extremely dehydrated	Yes

Once "sick" and "healthy" animals were identified and the images obtained were evaluates, 6 "healthy" pigs were selected from the same pen where the "sick" pig was located, making sure that these six pigs could be observed in all video recordings across the period analysed. As the pigs that were labelled "sick" (6 pigs in total) were observed to have symptoms in different periods across the study, each "sick" pig was paired with six "healthy" pigs from the same pen and during the same period, resulting in six groups (a total of 6 "sick" and 36 "healthy" pigs).

To determine the period that was analysed in each group, the day when pigs were labelled as "sick" (based on the clinical observations) was considered as "day 0" and 1-2 days before and after "day 0" were analysed to identify whether changes of eye-temperature, HR and RR were evident in "sick" pigs before signs of illness were visually detected. The days before "day 0" were labelled as negative numbers (e.g. -2 and -1) and the days after "day 0" were labelled as positive numbers (e.g. +1 and +2). Due to the routine management practices of the farm, some of the group/period included the day when pigs received prophylactic antimicrobial administered via water (every 2 weeks) or when the sick pig received a dose of injectable antibiotic (S6 only). When this occurred within the analysed period, it was recorded and considered in the observations.

Once the physiological parameters were obtained from each group/period, the trend of eye-temperature, HR and RR were evaluated within each group and the daily mean was calculated per pig. Analysis of variance tests were performed in order to evaluate the main effects (Block= groups; Treatment= health status). Plots of residuals vs fitted values were evaluated to assess the assumption of constant variance. The least significant difference (LSD) was used to test whether these physiological parameters were significantly different between "sick" and "healthy" pigs the day when symptoms were evident (day 0) and two days before (day -1 and day -2). The trend within these group/periods was also visually evaluated to observe whether the tendency of the physiological parameters differed between each "sick" pig (referred as S) and its paired "healthy" pigs (referred as H) across the analysed period (4-5 days; 25-30 measurements per day).

3. Outcomes

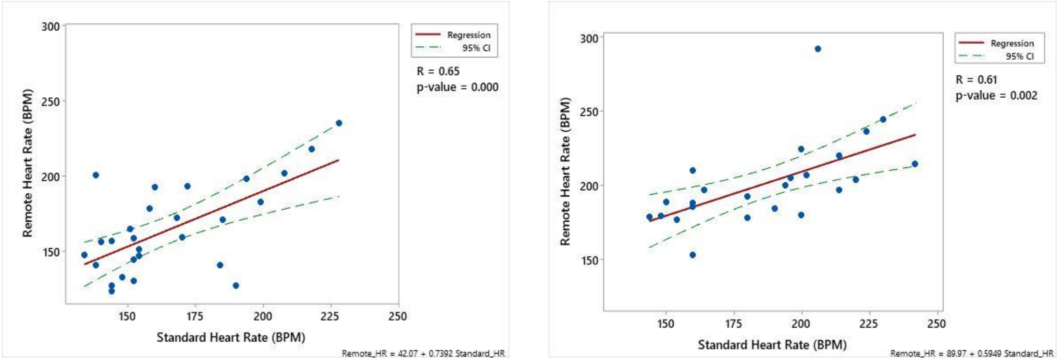
3.1. Part one: Validation study

The data from the comparison between the HR measured with stethoscope and the HR obtained from image processing from individual pigs showed good correlation, with similar correlation coefficients (r= 0.61 – 0.65) in both positions, being slightly higher when pigs were facing sideways of the camera (Table 2, Figure 3). When pigs were facing sideways, the computer-based technique, on average, under-estimated HR measures (Average Relative Error= 0.11). While the analysis of videos obtained when the face of pigs was towards the camera, on average, overestimated the HR measures (Average Relative Error= 0.11). Although inaccuracies may have occurred from analysis of video data, similarly some of the inaccuracy may have been caused by the challenge of manually counting heartrate with a stethoscope while a pig is being held. This also resulted in higher heart rates then when pigs are at rest, which may reduce the accuracy of measuring heart rate as has been shown by wearable heart rate monitors in people. Nevertheless, both orientations resulted in good correlations in measurements, which indicates that as long as the eye area is visible, HR measures of free moving pigs using RGB cameras can be recorded within a certain range of error. To our knowledge, no prior studies have investigated the use of similar techniques to measure HR of pigs. However, when comparing the present results to the results of a previous study in cattle [36], RGB imagery and computer-based methods appeared to be more accurate in pigs (r= 0.65) than in cattle (r= 0.18). This could be related to the low hair concentration and skin colour of pigs, which is more similar to the human face, where these techniques have been implemented in several studies with promising results [32,33,35,40]. The correlation between HR measures shown by the present study is lower than the correlation observed in humans by Takano and Ohta [41], who reported a correlation coefficient of 0.90 when comparing the human HR provided by pulse oximeters and the HR extracted by computer vision techniques that identified the change of brightness within the ROI (cheek). However, it was higher than the correlation reported by Cheng, *et al.* [42] when evaluating computer algorithms to assess human HR from RGB videos (r = 0.53). The studies that have implemented computer vision techniques over RGB videos to measure HR in humans normally involved the recording of people's face within a short distance, with minimum motion and controlled light conditions. Although pigs' motion and light condition are more difficult to control in farm settings, placing cameras in feeders or drinking stations could provide appropriate conditions and improve correlations, aiding a practical and more precise implementation of these techniques to assess HR changes in pigs.

Table 2. Pearson correlation coefficients (r) between heart rate (HR) and respiration rate (RR) obtained with standard methods (stethoscope and visual observations respectively) and image processing. Two different animal positions (toward and sideways) relative to the camera are compared.

Variable	Animal position	Method	Range	Mean (SD)	Correlation Coefficient (r)
HR (BPM)	Side	Stethoscope	134-228	165.89 (26)	0.65**
		C.V.	123-235	164.69 (30)	
	Front	Stethoscope	144-242	187.17 (29)	0.61*
		C.V.	152-291	201.32 (28)	
RR (BPM)	Side	Visual observation	39-53	46 (3)	0.61*
		C.V.	36-60	48 (6)	
	Front	Visual observation	36-53	42 (4)	0.66**
		C.V.	30-58	45 (9)	

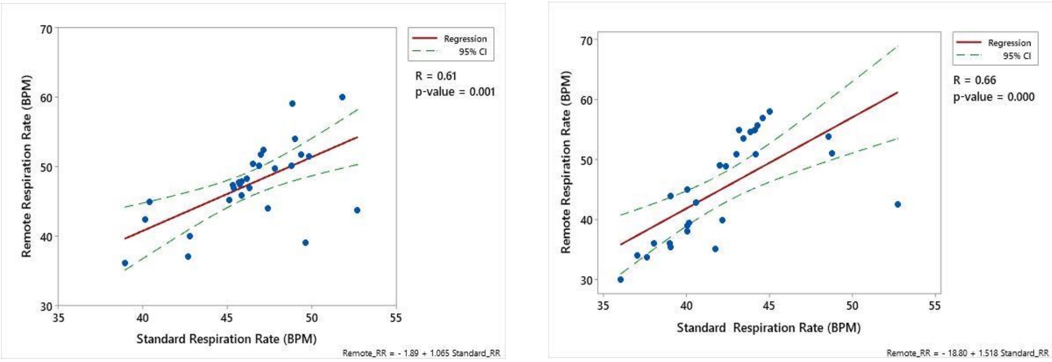
* ($p < 0.05$) ** ($p < 0.001$)



(**a**) (**b**)

Figure 3: Regression analysis of the relationship between heart rate (beats per minute) obtained with stethoscope (Standard Heart Rate) and the heart rate remotely obtained (Remote Heart Rate), when pigs were held in different positions; (a) facing sideways, (b) face towards the camera. The solid line shows the line of best fit, the dotted lines show the 95% CL. The equation and associated r and P-value are shown.

In the case of RR measures, these also showed good positive correlations between the standard and computer-based methods (r= 0.61 – 0.66), being slightly larger when the pigs faced towards the camera (Table 2, Figure 4). The computer-based technique, on average, overestimated the RR measures in both positions analysed (Average Relative Error= 0.08-0.13). Similarly to the present study, Stewart et. al. [25] investigated the use of TIR image recordings to identify the temperature changes within the nostrils to assess RR in cattle. The study of Stewart et. al. [25], similarly to the present study, reported good agreement between the standard and computer-based methods. However, their method involved the observation of the recordings and manual counting of air movement from the nostrils, while the present study involved the use of an algorithm to facilitate automatic recording. Pereira et al. [43] used TIR imagery to measure RR in anesthetised piglets by identifying the mechanical chest movements related to the respiratory cycle, showing great agreement with the RR measures recorded by the anaesthesia machine (mean absolute error averaged= 0.27±0.48 BPM). Although the correlation presented by the study above [43] was larger than the correlation presented in the present study, the methodology proposed by Pereira et al. [43] was implemented in anesthetised animals and was not affected by the motion and variable conditions present on commercial farms.



(**a**) (**b**)

Figure 4: Regression analysis of the relationship between respiration rate (breath per minute) obtained from visual observations (Standard Respiration Rate) and the heart rate remotely obtained (Remote Respiration Rate), when pigs were held in different positions; (a) facing sideways, (b) face towards the camera. The solid line shows the line of best fit, the dotted lines show the 95% CL. The equation and associated r and P-value are shown.

3.2. Part two: Early detection of respiratory diseases

The physiological parameters remotely assessed were compared across all groups (Table 3) and within each group (Figure 5; Figure 6; Figure 7).

Table 3. Summary of least significant difference (LSD) test between “sick” and “healthy” pigs, for eye-temperature (T), heart rate (HR) and respiration rate (RR). Indicating the difference between group during the day before (day -1) and the day when clinical signs were detected (day 0).

Variable	Day	Group	Mean	Least significant difference (LSD)	*p*-value
T (°C)	-1	Sick	38.97	0.39*	<0.001
		Healthy	37.81		
	0	Sick	39.11	0.35*	<0.001
		Healthy	37.78		
HR (BPM)	-1	Sick	83.62	3.12*	0.001
		Healthy	78.25		
	0	Sick	88.74	3.93*	<0.001
		Healthy	78.64		
RR (BPM)	-1	Sick	28.6	2.3	0.03
		Healthy	26.4		
	0	Sick	30.6	3.2*	0.006
		Healthy	26.4		

* Difference between groups is larger than LSD

When eye-temperature of "sick" and "healthy" pigs was analysed across all groups, the analysis of variance showed significantly ($p < 0.05$) higher eye-temperature in 'sick' pigs than in 'healthy' pigs from one day before the clinical symptoms were detected (Table 3). The daily average of eye-temperature in "sick" pigs was 1.2°C higher than "healthy" pigs (LSD= 0.39) the day before the symptoms were evident (day -1), and 1.3°C higher (LSD= 0.35) the day that clinical symptoms were detected (day 0). As eye-temperature has been suggested as a good indicator of core body temperature [22,44], this would indicate that pigs that are affected by respiratory infections have an increase in temperature around 24 hours before evident signs, such as cough, lethargy or anorexia among others are observed. These results are consistent with the results reported previously by Jorquera-Chavez et al. [37], who observed significantly higher eye-temperature in sick animals, compared to healthy animals the day after these pigs were inoculated with APP, and 6 hours before the detection of clinical symptoms. This is also consistent with the observations of Schaefer, et al. [10], who also compared clinical scores and temperatures obtained from TIR images for detecting early signs of bovine viral diarrhoea virus (BVDV) in calves, reporting clear changes in temperatures remotely obtained several days before clinical observations were identified in sick animals.

Although only one of the sick (S6) animals showed obvious signs of porcine respiratory disease (PRD) and was detected as sick by routine observations performed by stock people at the farm (treated and removed from the rest of the group), the eye-temperature appeared to be higher in most of the "sick" pigs (Figure 5). The day before evident symptoms (day -1), the average eye-temperature of most "sick" pigs (S1,S3,S4,S5,S6) was observed to differ significantly from the average eye-temperature of "healthy" pigs, with a difference ranging between 0.7 and 2.8°C (LSD= 0.39). Only one "sick" pig (S2) showed a non-significant difference (0.008 °C), which could be related to a lower level of infection in this pig compared to the rest of pigs. The day when symptoms were detected (day 0), the difference between all "sick" pigs and "healthy" pigs were significant and ranged between 0.6 and 2.9°C (LSD= 0.35).

In the case of HR, the analysis of variance showed significant difference ($p < 0.05$) of HR between "sick" and "healthy" pigs, across all groups. Similarly to eye-temperature, the difference of HR also became significant from one day before the day when clinical symptoms were detected (Table 3; Figure 6). The daily average of HR in "sick" pigs was 5.37 BPM higher than "healthy" pigs (LSD= 3.12) the day before the symptoms were evident (day -1), and 10.1 BPM higher (LSD= 3.93) the day that clinical symptoms were detected (day 0). This difference between "sick" and "healthy" animals agrees with studies that have suggested HR measures as an indication of illness in animals [45,46]. Moreover, the present results agree with several studies that have observed increased HR in animals presenting respiratory infections. For instance, Reinhold, et al. [47] showed that calves affected by *C. psittaci* infection increased their HR up to 160%, compared to the baseline. Weingartl, et al. [48] and Geisbert, et al. [49] reported fever and tachycardia as some of the first signs in horses inoculated with HeV. Furthermore, HR was observed to significantly increase in pigs challenged with *Actinobacillus pleuropneumoniae* (APP), before these pigs showed clinical signs [37].

Similarly to the observations on eye-temperature, the same "sick" pig (S2) showed a non-significant difference (2.48 BPM), when comparing the HR remotely-measured of “sick” and “healthy” pigs of the same group the day before evident symptoms were observed (day -1). In the case of the day when symptoms were detected (day 0), five of the groups showed a significant difference between the “sick” pigs and “healthy” pigs, ranging between 4.4 and 21.2 BPM. Pig S3 was the only “sick” pig that showed no significant difference (2.2 BPM) on day 0.

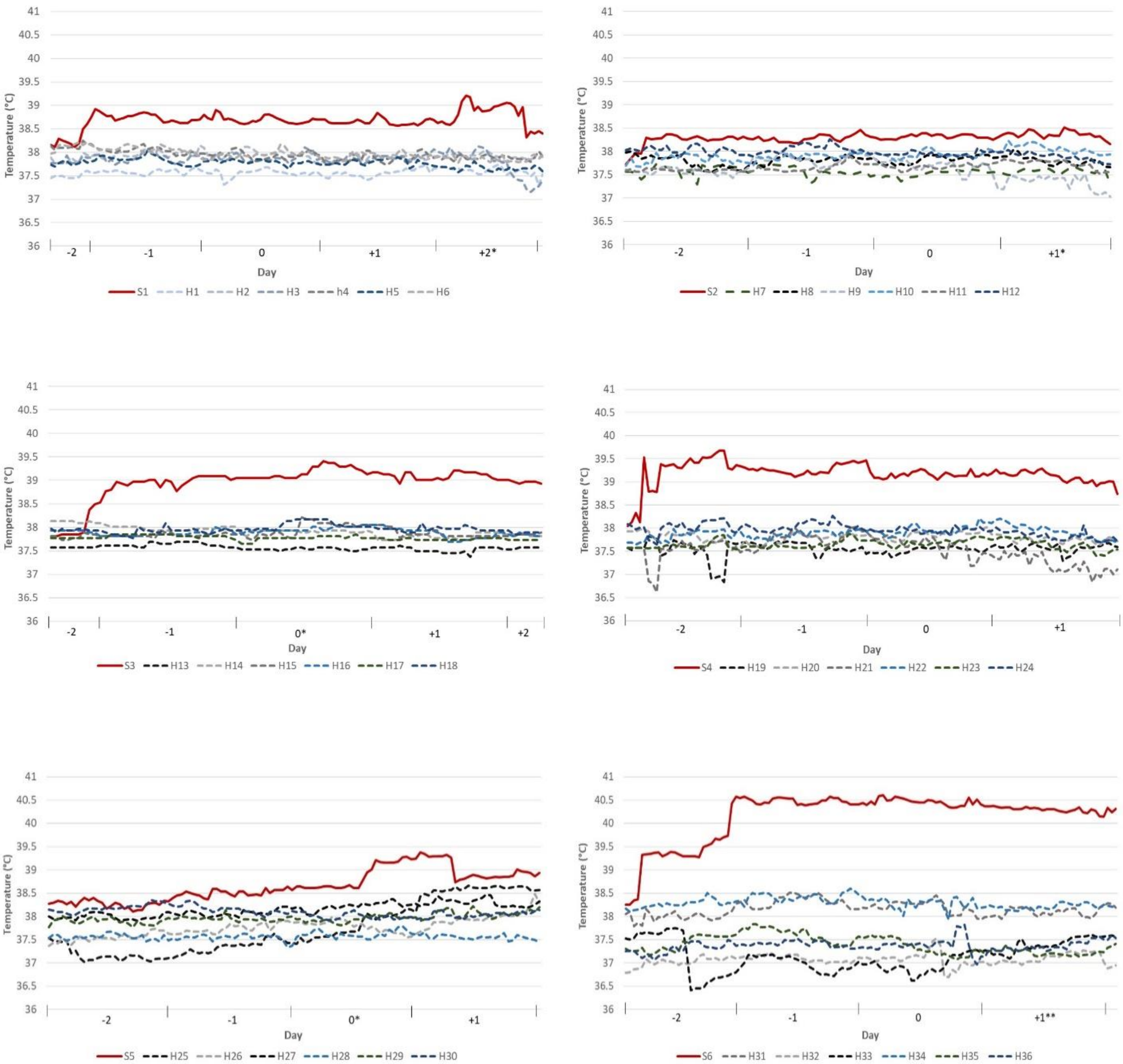


Figure 5. Measurements of eye temperature (degrees Celsius) in “sick” and “healthy” animals before and after clinical symptoms were detected. Each graph represents one group with one sick pig (red continuous line and labelled as S) and six healthy pigs (discontinuous lines and labelled as H). “Day 0” represents the day when clinical symptoms were detected. The symbol * indicates the day when antibiotic was administered via water, and ** indicates when a dose of injectable antibiotic was administrated to the sick pig.

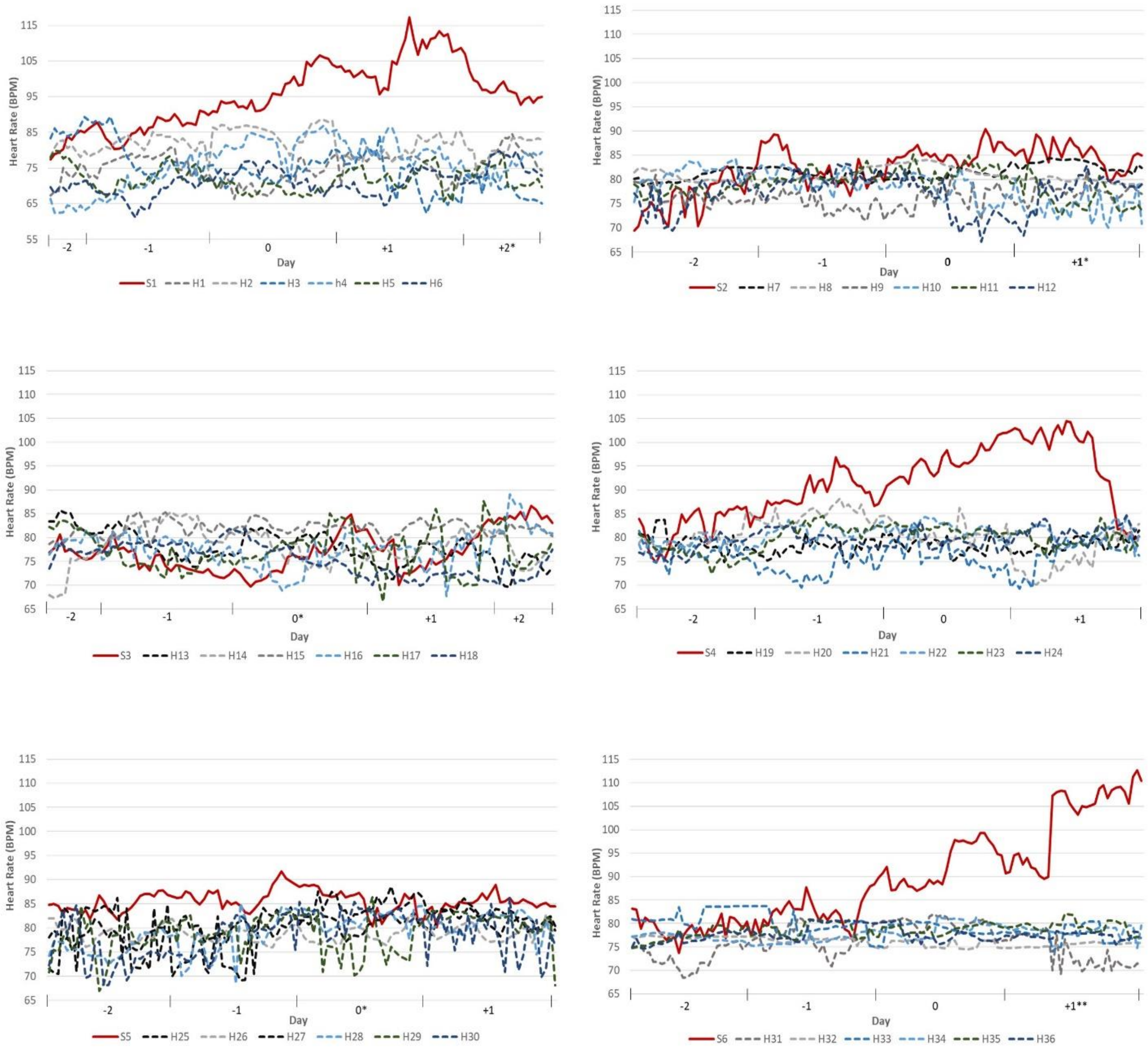


Figure 6. Measurements of heart rate (beats per minute) in "sick" and "healthy" animals before and after clinical symptoms were detected. Each graph represents one group with one sick pig (red continuous line and labelled as S) and six healthy pigs (discontinuous lines and labelled as H). The symbol * indicates the day when antibiotic was administered via water, and ** indicates when a dose of injectable antibiotic was administrated to the sick pig.

A different trend was observed in the RR measures within all groups (Table 3; Figure 7). From the analysis performed across groups, the daily average of RR was not observed to significantly differ between “sick” and “healthy” pigs the days before clinical symptoms were detected. However, the difference in RR between “sick” and “healthy” appeared to be significant the day when symptoms were detected in “sick” animals (day 0), when “sick” pigs had an average of RR 4.2 BPM higher than “healthy” pigs. These observations agree with a previous preliminary study [37], which also observed early changes of remotely-measured eye-temperature and HR in pigs infected with APP, while the remotely-measured RR of these pigs was observed to change at the same time that the clinical signs became evident to technicians. These results could indicate that the RR of pigs is affected during a more advanced stage of respiratory disease, which could be a result of the infection reaching the lungs. Although RR has been used as one of the signs to detect respiratory diseases [2,50], the results of the relationship between RR and the stage of these diseases varies between studies. For instance, Van Reeth et al. [50] found increased RR in pigs affected by influenza, 24 hours after being challenged with H1N2 virus, while Kerr et al. [2] did not find correlation between RR and calcitonin receptor (CTR) when using CTR as a sign of APP infection.

When analysing the trend of RR within each group, only three groups showed significantly higher RR ($p < 0.05$; LSD= 2.3) in “sick” animals than in “healthy” animals the day before clinical signs were detected in “sick” pigs (day -1). The most severe case (S6) was the one that showed the largest difference that day (S1= 2.6; S4= 2.9; S6= 14.4). The day when the signs of illness were detected in the “sick” pigs (day 0), all groups showed an increase on the difference of RR between “sick” and “healthy” pigs, with the most severe case (S6) reaching 22.6 BPM higher than the average of the “healthy” pigs. These differences can also be related to what was mentioned above, suggesting that evident changes of RR appear to occur in a more advanced stage of the respiratory disease. In addition, all these pigs were only showing mild effects of infection, with only S6 identified as sick and treated by farm staff.

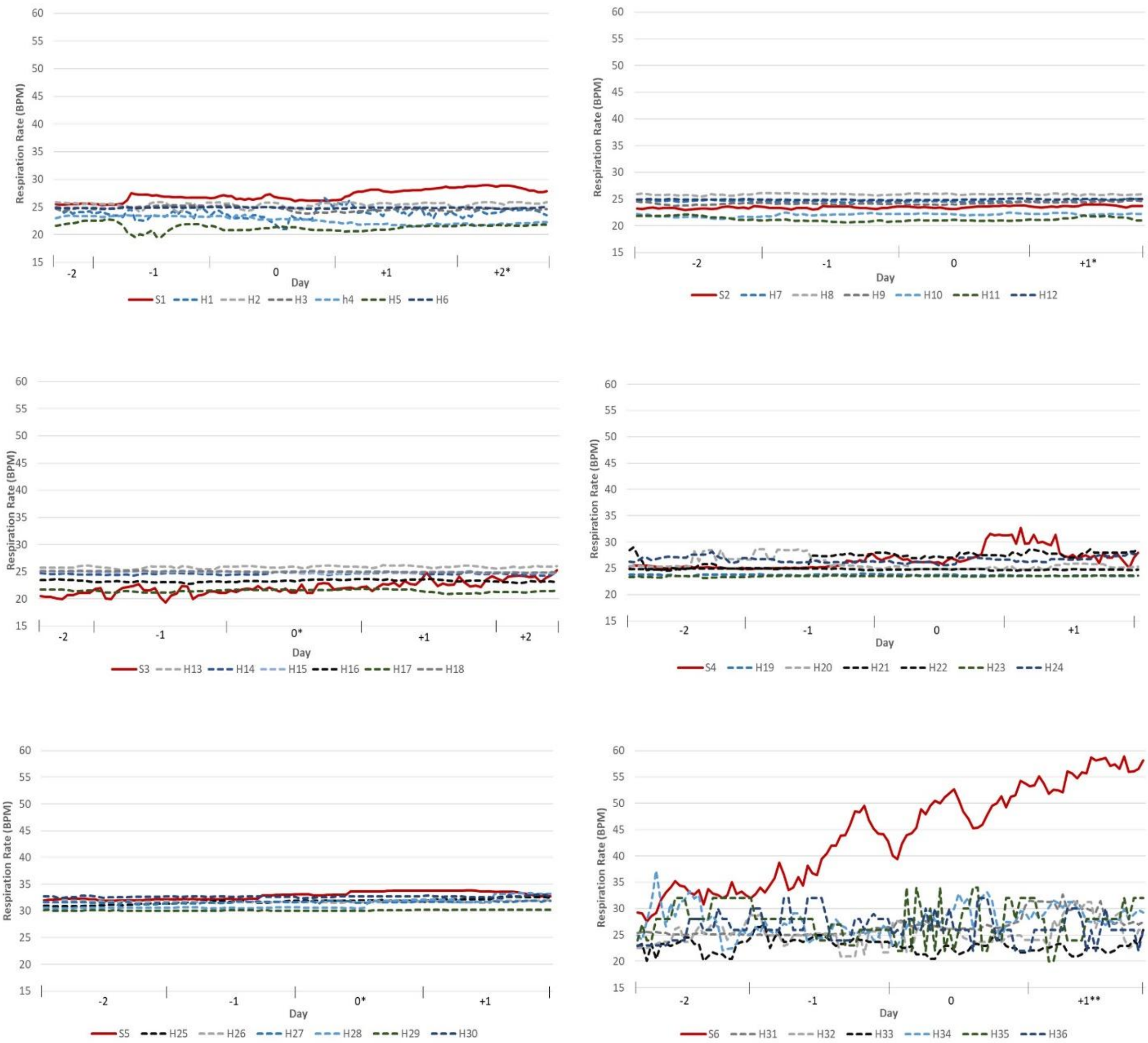


Figure 7. Measurements of respiration rate (breaths per minute) in "sick" and "healthy" animals before and after clinical symptoms were detected. Each graph represents one group with one sick pig (red continuous line and labelled as S) and six healthy pigs (discontinuous lines and labelled as H). The symbol * indicates the day when antibiotic was administered via water, and ** indicates when a dose of injectable antibiotic was administrated to the sick pig.

Considering the results shown above and the results obtained in a previous pilot study [37], these suggest that constant remote monitoring of physiological parameters could be a useful tool to detect signs of illness, before the routine monitoring performed on commercial farms will indicate the presence of ill pigs. Specifically, eye-temperature and HR seem to increase in affected pigs one or two days before other symptoms are visible in these pigs. Respiration rate on the other hand, appears to increase when other clinical signs are more visible. It is important to consider that these remotely-obtained measures were observed one or two days before clinical signs were detected from the observations of continuous recordings. Due to the normal workload and workflow of commercial piggeries, continuous monitoring is not possible and sick pigs are probably detected at a later stage. This could mean that remotely-monitored physiological parameters could indicate signs of illness even more than two days before the symptoms are detected by stock people. The detection of these early changes could improve the management of respiratory diseases in pigs, increasing the success of the treatment, and decreasing the rate of severe cases and death.

In addition to these results, it was also observed that these physiological parameters seemed to be influenced by environmental temperature. It was observed that these parameters were generally higher and more variable in the pigs included in the 5th (group of S5) and 6th (groups of S6) groups. This could be related to the environmental temperature registered during the period when these groups were analysed. The period analysed for the 5th group presented maximum ambient temperatures of ≥35 and the days included in the analysis of the 6th group presented maximum ambient temperatures of ≥38. Considering the influence that environmental conditions and individual characteristics have on the physiological parameters of pigs, these factors together with the comparison within the animal and across animals should be considering when studying the automatisation and implementation of this technology on farms for continuous monitoring and early detection of illness signs. Notwithstanding this variation in environmental conditions, early detection of respiratory disease was still possible with the use of the remote technologies used in this study.

Finally, not only the promising results, but also the limitations observed in the present study promote further research on the development, automatization and implementation of this technology to aid the continuous non-invasive monitoring of animals on commercial farms. Further development of validated algorithms would assist the application under the variable conditions on commercial farms, perhaps with the inclusion of individual and group data as well as environmental conditions. As mentioned above, it is hypothesized that the use of these cameras in feeder or drinker stations could be a good and practical approach for obtaining consistent and good quality images of the face, allowing the remote assessment of physiological changes in pigs.

4. Application of Research

The results of this pilot project are very encouraging and warrant further research on the development and implementation of imagery and computer-based methods as tools to constantly monitor pigs and other farm animals without the need of human interaction. These tools could aid the improvement of animal management and consequently animal health, animal welfare and productivity. Furthermore, the early detection of sick herds, and even more individual sick animals, would assist in improving the outcome of treatments and making the use of medications more effective.

5. Conclusion

Imagery and computer algorithms were validated to remotely measuring physiological parameters in pigs (HR and RR). Moreover, computer vision techniques appeared to be a useful tool to detect early physiological changes in pigs affected by respiratory diseases, before the symptoms can be observed by stock people, assisting the early detection and management of respiratory diseases in pigs. The changes in eye-temperature and heart rate remotely obtained showed clear differences between sick and healthy pigs during the period evaluated. However, significant changes of RR occurred only in a later stage of the illness.

Due to the observations resulted from this study, further research is suggested to investigate the development of algorithms and automatization of these techniques and the possible development of commercial monitoring systems.

6. Limitations/Risks

A limitation of the present project was the routine administration of antibiotics through the water every two weeks, which was part of the normal protocol on the farm. This limited the number of sick pigs and the severity of infection.

Only one pig was considered to be highly affected by respiratory infection, individually treated and removed from the pen. The other pigs that started showing signs of illness, which were considered sick in this study, showed a decrease of these signs shortly after the antibiotic was provided. Therefore, it was not possible to determine how remotely obtained parameters behave when there are severe cases of respiratory disease or multiple cases in the same pen.

7. Recommendations

As the results of this pilot study suggest the utility of computer vision technique to rapidly detect physiological changes related to disease in commercial pigs, further research is recommended. Further research should be focused toward continuing the development of algorithms and automatisation of this technology and investigating its use at a large-scale to test its performance detecting physiological changes of animals under different conditions and severity of disease.

Although the outcomes of the present study show very promising results, it is possible that cameras placed near drinkers may obtain even better quality and closer images of the face, possibly improving the image capture and processing, and aiding the assessment of changes in eye-temperature, HR and possibly RR of pigs. In addition, further research on the development of computer vision techniques over RGB videos to assess activity and behavioural changes is suggested in order to investigate whether the physiological changes together with automatically recorded behavioural changes can improve the detection and management of diseases in commercial piggeries.

Moreover, further research is recommended to advance the automatisation of these techniques and to evaluate how this automatisation can aid the development of a monitoring system able to detect and alert relevant changes related to the health and wellbeing status under commercial conditions. As mentioned above, to achieve this, it is important to study and consider the influence that individual characteristics and environmental conditions have on remotely-measured physiological parameter of animals. These factors, together with the individual and group tendency would need to be integrated into the automatization system in order to accurately detect when changes are related to wellbeing or health issues.

8. References

1. Cowton, J.; Kyriazakis, I.; Plotz, T.; Bacardit, J. A combined deep learning gru-autoencoder for the early detection of respiratory disease in pigs using multiple environmental sensors. *Sensors* **2018**, *18(8)*, 2521.
2. Kerr, C.A.; Eamens, G.; Briegel, J.; Sheehy, P.; Giles, L.; Jones, M. Effects of combined actinobacillus pleuropneumoniae challenge and change in environmental temperature on production, plasma insulin-like growth factor i (igf-i), and cortisol parameters in growing pigs. *Australian journal of agricultural research* **2003**, *54*, 1057-1064.
3. Opriessnig, T.; Giménez-Lirola, L.G.; Halbur, P.G. Polymicrobial respiratory disease in pigs. *Animal health research reviews* **2011**, *12*, 133-148.
4. Holt, H.R.; Alarcon, P.; Velasova, M.; Pfeiffer, D.U.; Wieland, B. Bpex pig health scheme: A useful monitoring system for respiratory disease control in pig farms? *BMC veterinary research* **2011**, *7*, 82.
5. Maes, D.; Sibila, M.; Kuhnert, P.; Segalés, J.; Haesebrouck, F.; Pieters, M. Update on mycoplasma hyopneumoniae infections in pigs: Knowledge gaps for improved disease control. *Transboundary and emerging diseases* **2018**, *65*, 110-124.
6. Jordan, D.; Chin, J.C.; Fahy, V.; Barton, M.; Smith, M.; Trott, D. Antimicrobial use in the australian pig industry: Results of a national survey. *Australian veterinary journal* **2009**, *87*, 222-229.
7. Barton, M.D. Impact of antibiotic use in the swine industry. *Current opinion in microbiology* **2014**, *19*, 9-15.
8. Lekagul, A. Patterns of antibiotic use in global pig production: A systematic review. *Veterinary and animal science* **2019**, 100058.
9. Gleeson, B.; Collins, A. Under what conditions is it possible to produce pigs without using antimicrobials? *Animal production science* **2015**, *55*, 1424-1431.
10. Schaefer, A.L.; Cook, N.; Tessaro, S.V.; Deregt, D.; Desroches, G.; Dubeski, P.L.; Tong, A.K.W.; Godson, D.L. Early detection and prediction of infection using infrared thermography. *Canadian journal of animal science* **2004**, 84(1), 73-80.

11. Ferrari, S.; Piccinini, R.; Silva, M.; Exadaktylos, V.; Berckmans, D.; Guarino, M. Cough sound description in relation to respiratory diseases in dairy calves. *Preventive veterinary medicine* **2010**, *96*, 276-280.
12. Polat, B.; Colak, A.; Cengiz, M.; Yanmaz, L.E.; Oral, H.; Bastan, A.; Kaya, S.; Hayirli, A. Sensitivity and specificity of infrared thermography in detection of subclinical mastitis in dairy cows. *Journal of dairy science* **2010**, *93*, 3525-3532.
13. Matthews, S.G.; Miller, A.L.; Clapp, J.; Plötz, T.; Kyriazakis, I. Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. *The veterinary journal* **2016**, *217*, 43-51.
14. Meiszberg, A.M.; Johnson, A.K.; Sadler, L.J.; Carroll, J.A.; Dailey, J.W.; Krebs, N. Drinking behavior in nursery pigs: Determining the accuracy between an automatic water meter versus human observers12. *Journal of animal science* **2009**, *87*, 4173-4180.
15. Andersen, H.-L.; Dybkjær, L.; Herskin, M.S. Growing pigs' drinking behaviour: Number of visits, duration, water intake and diurnal variation. *Animal* **2014**, *8*, 1881-1888.
16. Maselyne, J.; Adriaens, I.; Huybrechts, T.; De Ketelaere, B.; Millet, S.; Vangeyte, J.; Van Nuffel, A.; Saeys, W. 5. Assessing the drinking behaviour of individual pigs using rfid registrations. In *Precision livestock farming applications: Making sense of sensors to support farm management*, Wageningen Academic Publishers: 2015; pp 770-777.
17. Porto, S.M.; 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**, *115*, 184-194.
18. Matthews, S.G.; Miller, A.L.; PlÖtz, T.; Kyriazakis, I. Automated tracking to measure behavioural changes in pigs for health and welfare monitoring. *Scientific reports* **2017**, *7*, 17582.
19. Zheng, C.; Zhu, X.; Yang, X.; Wang, L.; Tu, S.; Xue, Y. Automatic recognition of lactating sow postures from depth images by deep learning detector. *Computers and electronics in agriculture* **2018**, *147*, 51-63.
20. Silva, M.; Ferrari, S.; Costa, A.; Aerts, J.-M.; Guarino, M.; Berckmans, D. Cough localization for the detection of respiratory diseases in pig houses. *Computers and electronics in agriculture* **2008**, *64*, 286-292.
21. Tabuaciri, P.; Bunter, K.L.; Graser, H.-U. In *Thermal imaging as a potential tool for identifying piglets at risk*, AGBU Pig Genetics Workshop. Armidale, Australia: Animal Genetics and Breeding Unit, University of New England, 2012; pp 23-30.
22. Soerensen, D.D.; Pedersen, L.J. Infrared skin temperature measurements for monitoring health in pigs: A review. *Acta veterinaria scandinavica* **2015**, *57*, 5.
23. Janžekovič, M.; Muršec, B.; Janžekovič, I. Techniques of measuring heart rate in cattle. *Tehnički vjesnik* **2006**, *13*, 31-37.
24. Eigenberg, R.; Hahn, G.; Nienaber, J.; Brown-Brandl, T.; Spiers, D. Development of a new respiration rate monitor for cattle. *Transactions of the ASAE* **2000**, *43*, 723.
25. Stewart, M.; Wilson, M.; Schaefer, A.; Huddart, F.; Sutherland, M. The use of infrared thermography and accelerometers for remote monitoring of dairy cow health and welfare. *Journal of dairy science* **2017**, *100*, 3893-3901.
26. Cooper-Prado, M.; Long, N.; Wright, E.; Goad, C.; Wettemann, R. Relationship of ruminal temperature with parturition and estrus of beef cows. *Journal of animal science* **2011**, *89*, 1020-1027.
27. Green, A.R.; Gates, R.S.; Lawrence, L.M. Measurement of horse core body temperature. *Journal of thermal biology* **2005**, *30*, 370-377.

28. Barbosa Pereira, C.; Kunczik, J.; Zieglowski, L.; Tolba, R.; Abdelrahman, A.; Zechner, D.; Vollmar, B.; Janssen, H.; Thum, T.; Czaplik, M. Remote welfare monitoring of rodents using thermal imaging. *Sensors* **2018**, *18*, 3653.
29. Rocha, L.M.; Devillers, N.; Maldague, X.; Kabemba, F.Z.; Fleuret, J.; Guay, F.; Faucitano, L. Validation of anatomical sites for the measurement of infrared body surface temperature variation in response to handling and transport. *Animals* **2019**, *9*, 425.
30. Schaefer, A.; Cook, N.; Bench, C.; Chabot, J.; Colyn, J.; Liu, T.; Okine, E.; Stewart, M.; Webster, J. The non-invasive and automated detection of bovine respiratory disease onset in receiver calves using infrared thermography. *Research in veterinary science* **2012**, *93*, 928-935.
31. Infrared thermography detects febrile and behavioural responses to vaccination of weaned piglets. *Animal* **2015**, *9*, 339-346.
32. Sikdar, A.; Behera, S.K.; Dogra, D.P. Computer-vision-guided human pulse rate estimation: A review. *IEEE reviews in biomedical engineering* **2016**, *9*, 91-105.
33. Li, X.; Chen, J.; Zhao, G.; Pietikainen, M. In *Remote heart rate measurement from face videos under realistic situations*, Proceedings of the IEEE conference on computer vision and pattern recognition, 2014; pp 4264-4271.
34. Barbosa Pereira, C.; Czaplik, M.; Blazek, V.; Leonhardt, S.; Teichmann, D. Monitoring of cardiorespiratory signals using thermal imaging: A pilot study on healthy human subjects. *Sensors* **2018**, *18*, 1541.
35. van der Kooij, K.M.; Naber, M. An open-source remote heart rate imaging method with practical apparatus and algorithms. *Behavior research methods* **2019**, *51*, 2106-2119.
36. Jorquera-Chavez, M.; Fuentes, S.; Dunshea, F.R.; Warner, R.D.; Poblete, T.; Jongman, E.C. Modelling and validation of computer vision techniques to assess heart rate, eye temperature, ear-base temperature and respiration rate in cattle. *Animals* **2019**, *9*, 1089.
37. Jorquera-Chavez, M.; Fuentes, S.; Dunshea, F.R.; Warner, R.D.; Poblete, T.; Morrison, R.S.; Jongman, E.C. Remotely sensed imagery for early detection of respiratory disease in pigs: A pilot study. *Animals* **2020**, *10*, 451.
38. Rashid, T.; Khawaja, H.A.; Edvardsen, K. Measuring thickness of marine ice using ir thermography. *Cold regions science and technology* **2019**, *158*, 221-229.
39. Schmidt, M.; Lahrmann, K.-H.; Ammon, C.; Berg, W.; Schön, P.; Hoffmann, G. Assessment of body temperature in sows by two infrared thermography methods at various body surface locations. *Journal of swine health and production* **2013**, *21*, 203-209.
40. Viejo, C.G.; Fuentes, S.; Torrico, D.D.; Dunshea, F.R. Non-contact heart rate and blood pressure estimations from video analysis and machine learning modelling applied to food sensory responses: A case study for chocolate. *Sensors* **2018**, *18*, 1802.
41. Takano, C.; Ohta, Y. Heart rate measurement based on a time-lapse image. *Medical engineering & physics* **2007**, *29*, 853-857.
42. Cheng, J.; Chen, X.; Xu, L.; Wang, Z.J. Illumination variation-resistant video-based heart rate measurement using joint blind source separation and ensemble empirical mode decomposition. *IEEE journal of biomedical and health informatics* **2017**, *21*, 1422-1433.
43. Pereira, C.B.; Dohmeier, H.; Kunczik, J.; Hochhausen, N.; Tolba, R.; Czaplik, M. Contactless monitoring of heart and respiratory rate in anesthetized pigs using infrared thermography. *PloS one* **2019**, *14*.

44. Gloster, J.; Ebert, K.; Gubbins, S.; Bashiruddin, J.; Paton, D.J. Normal variation in thermal radiated temperature in cattle: Implications for foot-and-mouth disease detection. *BMC veterinary research* **2011**, *7*, 73.
45. Jackson, P.; Cockcroft, P. *Clinical examination of farm animals*. John Wiley & Sons: 2008.
46. Reyes-Lagos, J.J.; Hadamitzky, M.; Peña-Castillo, M.Á.; Echeverría, J.C.; Bösche, K.; Lückemann, L.; Schedlowski, M.; Pacheco-López, G. Exogenous oxytocin reduces signs of sickness behavior and modifies heart rate fluctuations of endotoxemic rats. *Physiology & behavior* **2016**, *165*, 223-230.
47. Reinhold, P.; Ostermann, C.; Liebler-Tenorio, E.; Berndt, A.; Vogel, A.; Lambertz, J.; Rothe, M.; Rüttger, A.; Schubert, E.; Sachse, K. A bovine model of respiratory chlamydia psittaci infection: Challenge dose titration. *PloS one* **2012**, *7*, e30125.
48. Weingartl, H.M.; Berhane, Y.; Czub, M. Animal models of henipavirus infection: A review. *The veterinary journal* **2009**, *181*, 211-220.
49. Geisbert, T.W.; Feldmann, H.; Broder, C.C. Animal challenge models of henipavirus infection and pathogenesis. In *Henipavirus*, Springer: 2012; pp 153-177.
50. Van Reeth, K.; Gregory, V.; Hay, A.; Pensaert, M. Protection against a european h1n2 swine influenza virus in pigs previously infected with h1n1 and/or h3n2 subtypes. *Vaccine* **2003**, *21*, 1375-1381.

Appendices

Appendix 1:

animals

MDPI

Article

Remotely Sensed Imagery for Early Detection of Respiratory Disease in Pigs: A Pilot Study

Maria Jorquera-Chavez [1,*], Sigfredo Fuentes [1], Frank R. Dunshea [1], Robyn D. Warner [1], Tomas Poblete [1], Rebecca S. Morrison [2] and Ellen C. Jongman [3]

[1] Faculty of Veterinary and Agricultural Sciences, University of Melbourne, VIC 3010, Australia; sigfredo.fuentes@unimelb.edu.au (S.F.); fdunshea@unimelb.edu.au (F.R.D.); robyn.warner@unimelb.edu.au (R.D.W.); tomas.poblete@unimelb.edu.au (T.P.)

[2] Research and Innovation, Rivalea (Australia) Pty. Ltd., Corowa, NSW 2646, Australia; RMorrison@rivalea.com.au

[3] Animal Welfare Science Centre, Faculty of Veterinary and Agricultural Sciences, University of Melbourne, Parkville, VIC 3010, Australia; ejongman@unimelb.edu.au

* Correspondence: mjorquera@student.unimelb.edu.au; Tel.: +61-413-628-813

Received: 15 February 2020; Accepted: 6 March 2020; Published: 9 March 2020

check for updates

Simple Summary: Respiratory disease in pigs causes suffering in infected animals and economic losses to producers. One of the most appropriate approaches to minimising these negative effects is by the early detection of infected animals. This pilot study aimed to use computer-based techniques to measure changes in temperature (eye and ear-base temperature), heart rate and respiration rate of pigs from thermal-infrared and conventional images. These measures, together with clinical observations, were obtained from pigs that were infected with *Actinobacillus pleuropneumoniae* (APP) and from pigs that were healthy. Infected pigs showed higher temperature and heart rate than healthy pigs across the period analysed. Respiration rate showed less difference between infected and healthy pigs. In addition, the biggest changes in these measures were recorded from six hours before the clinical observations identified sick animals. Results have highlighted that computer vision techniques can provide important and useable data regarding physiological changes that can indicate early signs of respiratory infection in pigs. This could aid the management of the disease, increasing the success of the treatment and decreasing the rate of severe cases and death.

Abstract: Respiratory diseases are a major problem in the pig industry worldwide. Due to the impact of these diseases, the early identification of infected herds is essential. Computer vision technology, using RGB (red, green and blue) and thermal infrared imagery, can assist the early detection of changes in animal physiology related to these and other diseases. This pilot study aimed to identify whether these techniques are a useful tool to detect early changes of eye and ear-base temperature, heart rate and respiration rate in pigs that were challenged with *Actinobacillus pleuropneumoniae*. Clinical observations and imagery were analysed, comparing data obtained from animals that showed some signs of illness with data from animals that showed no signs of ill health. Highly significant differences ($p < 0.05$) were observed between sick and healthy pigs in heart rate, eye and ear temperature, with higher heart rate and higher temperatures in sick pigs. The largest change in temperature and heart rate remotely measured was observed around 4–6 h before signs of clinical illness were observed by the skilled technicians. These data suggest that computer vision techniques could be a useful tool to detect indicators of disease before the symptoms can be observed by stock people, assisting the early detection and control of respiratory diseases in pigs, promoting further research to study the capability and possible uses of this technology for on farm monitoring and management.

Keywords: animal monitoring; imagery; computer vision; animal health; symptoms; physiological changes

Animals 2020, *10*, 451; doi:10.3390/ani10030451 www.mdpi.com/journal/animals

Appendix 2:

animals

MDPI

Article

Modelling and Validation of Computer Vision Techniques to Assess Heart Rate, Eye Temperature, Ear-Base Temperature and Respiration Rate in Cattle

Maria Jorquera-Chavez [1,*], Sigfredo Fuentes [1], Frank R. Dunshea [1], Robyn D. Warner [1], Tomas Poblete [1] and Ellen C. Jongman [2]

[1] Faculty of Veterinary and Agricultural Sciences, University of Melbourne, Melbourne, VIC 3010, Australia; sigfredo.fuentes@unimelb.edu.au (S.F.); fdunshea@unimelb.edu.au (F.R.D.); robyn.warner@unimelb.edu.au (R.D.W.); totopoblete@gmail.com (T.P.)

[2] Animal Welfare Science Centre, Faculty of Veterinary and Agricultural Sciences, University of Melbourne, Parkville, VIC 3010, Australia; ejongman@unimelb.edu.au

[*] Correspondence: mjorquera@student.unimelb.edu.au; Tel.: +61-413-628-813

Received: 5 November 2019; Accepted: 4 December 2019; Published: 6 December 2019

check for updates

Simple Summary: Animal monitoring normally requires procedures that are time- and labour-consuming. The implementation of novel non-invasive technologies could be a good approach to monitor animal health and welfare. This study aimed to evaluate the use of images and computer-based methods to track specific features of the face and to assess temperature; respiration rate and heart rate in cattle. The measurements were compared with measures obtained with conventional methods during the same time period. The data were collected from ten dairy cows that were recorded during six handling procedures across two consecutive days. The results from this study show over 92% of accuracy from the computer algorithm that was developed to track the areas selected on the videos collected. In addition, acceptable correlation was observed between the temperature calculated from thermal infrared images and temperature collected using intravaginal loggers. Moreover, there was acceptable correlation between the respiration rate calculated from infrared videos and from visual observation. Furthermore, a low to high relationship was found between the heart rate obtained from videos and from attached monitors. The study also showed that both the position of the cameras and the area analysed on the images are very important, as both had large impact on the accuracy of the methods. The positive outcomes and the limitations observed in this study suggest the need for further research

Abstract: Precision livestock farming has emerged with the aim of providing detailed information to detect and reduce problems related to animal management. This study aimed to develop and validate computer vision techniques to track required features of cattle face and to remotely assess eye temperature, ear-base temperature, respiration rate, and heart rate in cattle. Ten dairy cows were recorded during six handling procedures across two consecutive days using thermal infrared cameras and RGB (red, green, blue) video cameras. Simultaneously, core body temperature, respiration rate and heart rate were measured using more conventional 'invasive' methods to be compared with the data obtained with the proposed algorithms. The feature tracking algorithm, developed to improve image processing, showed an accuracy between 92% and 95% when tracking different areas of the face of cows. The results of this study also show correlation coefficients up to 0.99 between temperature measures obtained invasively and those obtained remotely, with the highest values achieved when the analysis was performed within individual cows. In the case of respiration rate, a positive correlation (r = 0.87) was found between visual observations and the analysis of non-radiometric infrared videos. Low to high correlation coefficients were found between the heart rates (0.09–0.99) obtained from attached monitors and from the proposed method. Furthermore, camera location and the area analysed appear to have a relevant impact on the performance of the proposed techniques. This

Animals 2019, 9, 1089; doi:10.3390/ani9121089 www.mdpi.com/journal/animals