Using imagery and computer vision as remote monitoring methods for early detection of respiratory disease in pigs

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Abstract

Respiratory diseases in pigs impact the wellbeing of animals and increase the cost of production. One of the most appropriate approaches to minimizing these negative effects is the early detection of ill animals. The use of cameras coupled with computer-based techniques could assist the early detection of physiological changes in pigs when they are beginning to become ill and prior to exhibiting clinical signs. This study consisted of two experiments that aimed to (a) evaluate the use of computer-based techniques over RGB (red, green, and blue) and thermal infrared imagery to measure heart rate and respiration rate of pigs, and (b) to investigate whether eye-temperature, heart rate and respiration rate assessed remotely could be used to identify early signs of respiratory diseases in free-moving, and group-housed growing pigs in a commercial piggery. In the first experiment, the remotely-obtained heart rate and respiration rate were compared with the measures obtained with standard methods, showing positive correlations ($r = 0.61 – 0.66$; $p < 0.05$). In the second experiment, pigs were recorded by overhead cameras and the remotely-obtained physiological measures were analysed to identify whether physiological changes could be detected in sick pigs before clinical signs were observed. The changes in eye-temperature and heart rate remotely obtained showed clear differences between sick and healthy pigs two days before clinical signs were detected. While significant changes in respiration rate occurred the day before clinical signs of illness were identified. The results of the present study indicate the possible use of computer vision technique for constant animal monitoring and rapid detection of physiological changes related to illness in commercial pigs. Further research is recommended to continue the development, automatization, and commercial practicality of this novel technology.

Keywords: Animal monitoring; non-invasive methods; contactless monitoring; animal health; physiological indicators.

1. Introduction

The detection of health challenges affecting pigs is critical in maintaining appropriate levels of health and animal welfare within commercial piggeries. The early detection of illnesses is crucial to reduce the impact that these diseases have on the animals and the industry, and to increase the success of the treatments applied (Cowton et al., 2018). Pleuropneumonia is one of the diseases that greatly impacts the pig industry to a large part because it can easily propagate across pigs (Kerr et al., 2003). These diseases reduce the wellbeing of pigs and increase the cost of production through their effect on weight gain and death observed in affected pigs, as well as the increased use of antibiotics to prevent and treat these infections (Opriessnig et al., 2011; Maes et al., 2018).

The pig industry is developing new early disease intervention and management tools to enable early disease identification, facilitating responsible antibiotic stewardship, reducing the risk of antimicrobial resistance (Lekagul, 2019; Jorquera-Chavez et al., 2020).

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 examinations (Schaefer et al., 2004). Novel non-invasive methods are being investigated in an attempt to overcome these limitations and assist stock people in detecting diseases at an early stage and take rapid action, minimising the propagation of the infection within the herd and reducing the use of medical treatments (Ferrari et al., 2010). 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, coughing sounds and skin temperature have been investigated for applications to detect illness in several species (Matthews et al., 2016; Matthews et al., 2017).

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 (Soerensen and Pedersen, 2015; Stewart et al., 2017).

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 Kalantar-Zadeh et al., 2016) and infrared thermal (IRT) cameras (Rocha et al., 2019) have been studied to detect trends and relevant changes in body temperature of several species. For instance, Schaefer et al. (2012) indicated IRT images to be a useful tool to detect high temperatures related to bovine respiratory disease complex (BRD).

The measurement of HR and RR of animal 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 (Barbosa Pereira et al., 2018; van der Kooij and Naber, 2019). Although these methods have been less explored in animals, some studies have investigated the possible use of RGB (red, green and blue) and IRT imagery to assess HR and RR in farm animals (Stewart et al., 2017; Jorquera-Chavez et al., 2019; Jorquera-Chavez et al., 2020).

Considering the impact that respiratory diseases have on the pig industry and the challenges related to its detection and treatment, this study investigated the use of IRT cameras and video cameras in a commercial indoor piggery. This study had the aim of (a) evaluating the proposed algorithms to measure HR and RR in pigs and (b) 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 stock people. The result of this study 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 study. These combine a high resolution radiometric thermal sensor and a 4K visible RGB sensor. The IRT sensor had a spectral range of 7.5 – 13.5 µm, sensitivity < 50 mK, resolution of 640 x 512 pixels, emissivity of 0.985, and a frame rate of 30 Hz per second. The RGB sensor had a resolution of 4000 x 3000 pixels and a frame rate of 30 Hz per second. The average temperature and humidity obtained from the closest meteorological station was included in the settings of the camera. As the second part of this study required continuous monitoring, a storage system was developed using Raspberry Pi (Raspberry Pi Foundation, Cambridge, UK).

Collected images were processed using customised algorithms developed in Matlab® R2018b (Mathworks Inc. Natick, MA, USA). In the case of IRT images, this algorithm firstly extracted the radiometric information of each image, by using FLIR® Atlas SDK (FLIR Systems, Wilsonville, OR. USA) (Jorquera-Chavez et al., 2019). 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 IRT images to measure body temperature (Soerensen and Pedersen, 2015).

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, as reported by Jorquera-Chavez et al. (2019). 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 (van der Kooij and Naber, 2019). To assess HR in the present study, the eye area was used as ROI because it presents a low density of hair, and because this area has been shown to be useful when using imagery in humans and animals (Soerensen and Pedersen, 2015).

Furthermore, for the analysis of respiration rate IRT images were processed, using the nose area as ROI. Similarly to the HR analysis, the ROI (nose area) was 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 were 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 (Jorquera-Chavez et al., 2019).

2.2. Animals and data 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 study was divided into two experiments. The "First experiment" refers to the evaluation of the proposed techniques, while the "Second experiment" refers to the implementation of these techniques for early detection of respiratory diseases in pigs under commercial conditions.

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

2.2.1. First experiment: Evaluation of the proposed methods

A total of twenty-eight, post-weaned pigs, at 9 weeks of age, were grouped into two adjacent pens (3.5m x 2.8m per pen). 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 (Fig. 1). 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.

Fig. 1. Description of camera position. Cameras located at a height of 2.5 metres, each camera directed towards a respective pen.

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 quietly by a technician for one minute with the face towards the camera, and another minute facing sideways to 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 pigs 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. Second experiment: Early detection of respiratory diseases

Two groups of 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 3.5m 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 3.5m x 2.8m (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 (Fig. 1). 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 from evening to early morning. Recordings were obtained during 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 identified using stock marker, being 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 clinical observations (Table 1), which were performed daily by farm technicians (as part of their normal routine) and during one hour every 7 days by an external technician, 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 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 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 evaluated, 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 health management practices of the farm, the sick pig received a dose of injectable antibiotic (S6 only). When this treatment 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 Genstat® 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). Following this analysis, further ANOVA tests were performed in Genstat® including the average obtained in each day (-2, -1 and 0) and the average obtained in two periods of each day (AM and PM) in order to identify in what period of the day the difference in physiological parameters between “sick” and “healthy” pigs became apparent.

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. Results and Discussion

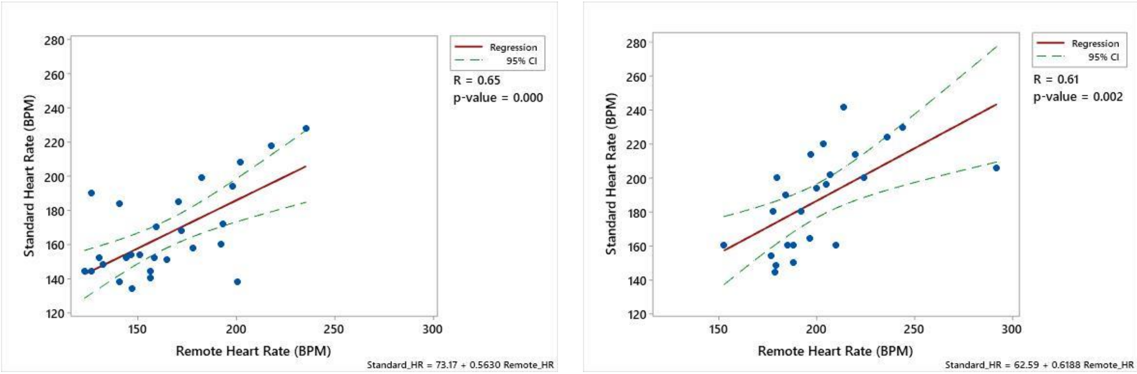
3.1. First experiment: Evaluation of the proposed methods

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 to the camera (Table 2, Fig. 2). 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 the video data, some of the inaccuracy may have been caused by the challenge of manually counting heartrate with a stethoscope while a pig was being held. 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. 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 (Jorquera-Chavez et al., 2019), 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 hair concentration and skin colour of pigs, among other similarities that have been shown between porcine and human skin (Simon and Maibach, 2000; Jacobi et al., 2007), in which these techniques have been implemented in several studies with promising results (Viejo et al., 2018; van der Kooij and Naber, 2019). The correlation between HR measures shown in the present study is lower than the correlation observed in humans by Takano and Ohta (2007), 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. (2017) 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, 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 (C.V.). 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)	

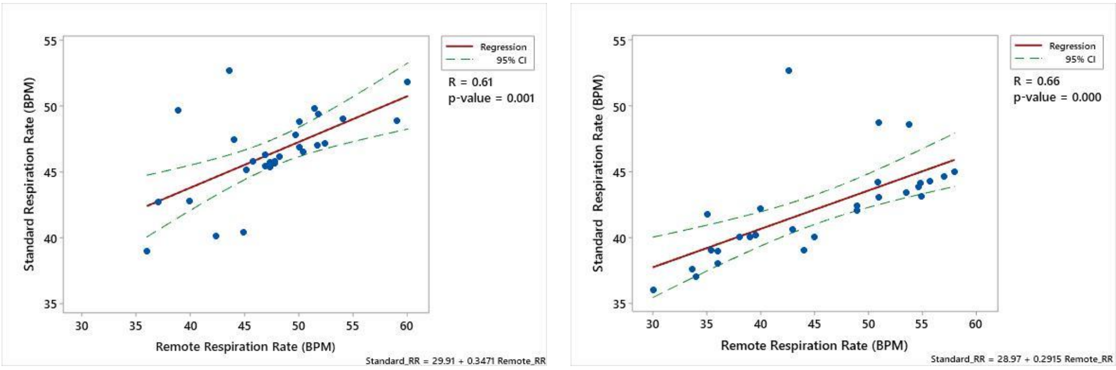
* ($p < 0.05$) ** ($p < 0.001$)



(a) (b)

Fig. 2. 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 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, Fig. 3). 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. (2017) investigated the use of IRT image recordings to identify the temperature changes within the nostrils to assess RR in cattle. The study of Stewart et al. (2017), 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. (2019) used IRT 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 anesthesia machine (mean absolute error averaged= 0.27±0.48 BPM). Although the correlation presented by the study above was larger than the correlation presented in the present study, the methodology proposed by Pereira et al. (2019) was implemented in anesthetised animals and was not affected by the motion and variable conditions present on commercial farms.



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

Fig. 3. 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. Second experiment: Early detection of respiratory diseases

The physiological parameters remotely assessed were compared across all groups and within each group.

When eye-temperature of “sick” and “healthy” pigs was analysed across all groups, the ANOVA showed significantly ($p< 0.05$) higher eye-temperature in “‘sick” pigs than in “healthy” pigs from two days before the clinical symptoms were detected (Table 3). The daily average of eye-temperature in “sick” pigs was 0.8 °C higher than “healthy” pigs two days before the symptoms were evident (day -2), 1.28 °C the day before the symptoms were evident (day -1), and 1.34 °C higher on the day that clinical symptoms were detected (day 0).

When the ANOVA included the period of the day for this comparison, day/health ($p< 0.001$) and day/period/health interactions ($p< 0.01$) were observed. In addition, eye-temperature showed significant changes from the morning (AM) of the second last day (day -2) before clinical signs were detected in ill pigs (Table 3). As eye-temperature has been suggested as a good indicator of core body temperature (Soerensen and Pedersen, 2015), this would indicate that pigs that are affected by respiratory infections have an increase in temperature around 48 hours before evident signs, such as cough, lethargy or refusing to eat. These results are consistent with the results reported previously by Jorquera-Chavez et al. (2020), who observed significantly higher eye-temperature in sick animals, compared to healthy animals the day after these pigs were inoculated with *Actinobacillus pleuropneumoniae* (APP), and 6 hours before the detection of clinical symptoms. This is also consistent with the observations of Schaefer et al. (2004), who also compared clinical scores and temperatures obtained from IRT 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.

Table 3. Summary of eye-temperature (T) means in the morning, afternoon and the average morning-afternoon obtained two days before (-2), the day before (day -1) and the day when clinical signs were detected (day 0). Least significant difference (LSD) is shown at the 0.05 level.

Variable	Day	Period	Group	Mean	Day average	L.S.D.
T (°C)	-2	Morning	Sick	38.33	38.53	0.34†‡*
		Afternoon		38.72		
		Morning	Healthy	37.72	37.73	
		Afternoon		37.73		
	-1	Morning	Sick	39.04	39.07	0.34†‡*
		Afternoon		39.09		
		Morning	Healthy	37.78	37.79	
		Afternoon		37.8		
	0	Morning	Sick	39.06	39.12	0.34†‡*
		Afternoon		39.17		
		Morning	Healthy	37.75	37.78	
		Afternoon		37.80		

† Difference between groups is larger than LSD in the respective morning.
‡ Difference between groups is larger than LSD in the respective afternoon.
* Difference between groups is larger than LSD in the respective day.

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 (first aid performed and removed and placed in a recovery pen), the eye-temperature appeared to be higher in most of the "sick" pigs (Appendix Fig. A1). 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 also showed day/health ($p < 0.001$) and day/period/health interactions ($p < 0.05$). The difference of HR became significant from the afternoon of the second last day before the day when clinical symptoms were detected (Table 4; Appendix Fig. A2), being the HR of "sick" pigs 4.3 BPM higher than in "healthy" pigs (LSD= 3.7) that afternoon. The day before the symptoms were evident (day -1) the HR of "sick" pigs was 5.3 BPM higher than "healthy" pigs, and 10.8 BPM higher 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 (Reyes-Lagos et al., 2016). Moreover, the present results agree with several studies that have observed increased HR in animals presenting respiratory infections. For instance, Reinhold et al. (2012) showed that calves affected by *C. psittaci* infection increased their HR up to 160%, compared to the baseline. Weingartl et al. (2009) and Geisbert et al. (2012) reported fever and tachycardia as some of the first signs in horses inoculated with the Hendra virus (HeV). Furthermore, HR was observed to significantly increase in pigs challenged with *Actinobacillus pleuropneumoniae* (APP), before these pigs showed clinical signs (Jorquera-Chavez et al., 2020).

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.

Table 4. Summary of heart rate (HR) means in the morning, afternoon and the average morning-afternoon obtained two days before (-2), the day before (day -1) and the day when clinical signs were detected (day 0). Least significant difference (LSD) is shown at the 0.05 level.

Variable	Day	Period	Group	Mean	Day average	L.S.D.
HR (BPM)	-2	Morning	Sick	78.60	80.43	3.7‡
		Afternoon		82.26		
		Morning	Healthy	77.44	77.72	
		Afternoon		77.99		
	-1	Morning	Sick	83.86	83.80	3.7†‡*
		Afternoon		83.73		
		Morning	Healthy	78.12	78.46	
		Afternoon		78.8		
	0	Morning	Sick	86.29	89.79	3.7†‡*
		Afternoon		93.28		
		Morning	Healthy	79.11	79.01	
		Afternoon		78.90		

† Difference between groups is larger than LSD in the respective morning.
‡ Difference between groups is larger than LSD in the respective afternoon.
* Difference between groups is larger than LSD in the respective day.

A different trend was observed in the RR measures within all groups (Table 5). From the analysis performed across groups, considering the day and period of the day, RR was not observed to significantly differ between "sick" and "healthy" pigs the second last day before clinical symptoms were detected. However, the difference in RR between "sick" and "healthy" appeared to be significant the afternoon of the day before symptoms were detected in "sick" animals (day -1), when "sick" pigs had an average of RR 3.6 BPM higher than "healthy" pigs (LSD= 2.84). In addition, day by health interaction ($p< 0.001$) was found. These observations agree with a previous preliminary study (Jorquera-Chavez et al., 2020), 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 compromising the lungs. Although RR has been used as one of the signs to detect respiratory diseases, the results of the relationship between RR and the stage of these diseases varies between studies. For instance, Van Reeth et al. (2003) found increased RR in pigs affected by influenza, 24 hours after being challenged with H1N2 virus, while Kerr et al. (2003) did not find correlation between RR and calcitonin receptor (CTR) when using CTR as a sign of APP infection.

Table 5. Summary of respiration rate (RR) means in the morning, afternoon and the average morning-afternoon obtained two days before (-2), the day before (day -1) and the day when clinical signs were detected (day 0). Least significant difference (LSD) is shown at the 0.05 level.

Variable	Day	Period	Group	Mean	Day average	L.S.D.
RR (BPM)	-2	Morning	Sick	26.00	26.37	2.84
		Afternoon		26.74		
		Morning	Healthy	25.62	25.67	
		Afternoon		25.71		
	-1	Morning	Sick	27.05	28.17	2.84‡
		Afternoon		29.29		
		Morning	Healthy	25.74	25.73	
		Afternoon		25.71		
	0	Morning	Sick	29.66	30.63	2.84†‡*
		Afternoon		31.59		
		Morning	Healthy	25.83	25.85	
		Afternoon		25.87		

† Difference between groups is larger than LSD in the respective morning.
‡ Difference between groups is larger than LSD in the respective afternoon.
* Difference between groups is larger than LSD in the respective day.

When analysing the trend of RR within each group (Appendix Fig. A3), only three groups showed significantly higher RR ($p < 0.05$) 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 stock people.

Considering the results shown above and the results obtained in a previous pilot study (Jorquera-Chavez et al., 2020), 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 are able to indicate the presence of ill pigs. Specifically, eye-temperature and HR seem to increase in affected pigs two days before other symptoms are visible in these pigs. Respiration rate on the other hand, appears to increase hours before 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. This research potentially shows that remotely-monitored physiological parameters could indicate signs of illness even more than two days before the physical 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 medical 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 °C and the days included in the analysis of the 6th group presented maximum ambient temperatures of ≥38 °C. 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 considered 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.

4. Conclusion

Imagery and computer algorithms were evaluated to remotely measure physiological parameters in pigs (heart rate and respiration rate). 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 in respiration rate occurred at a later stage of onset of the illness.

Based on the positive observations 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.

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Appendix A. Evaluation of trends within each group/period

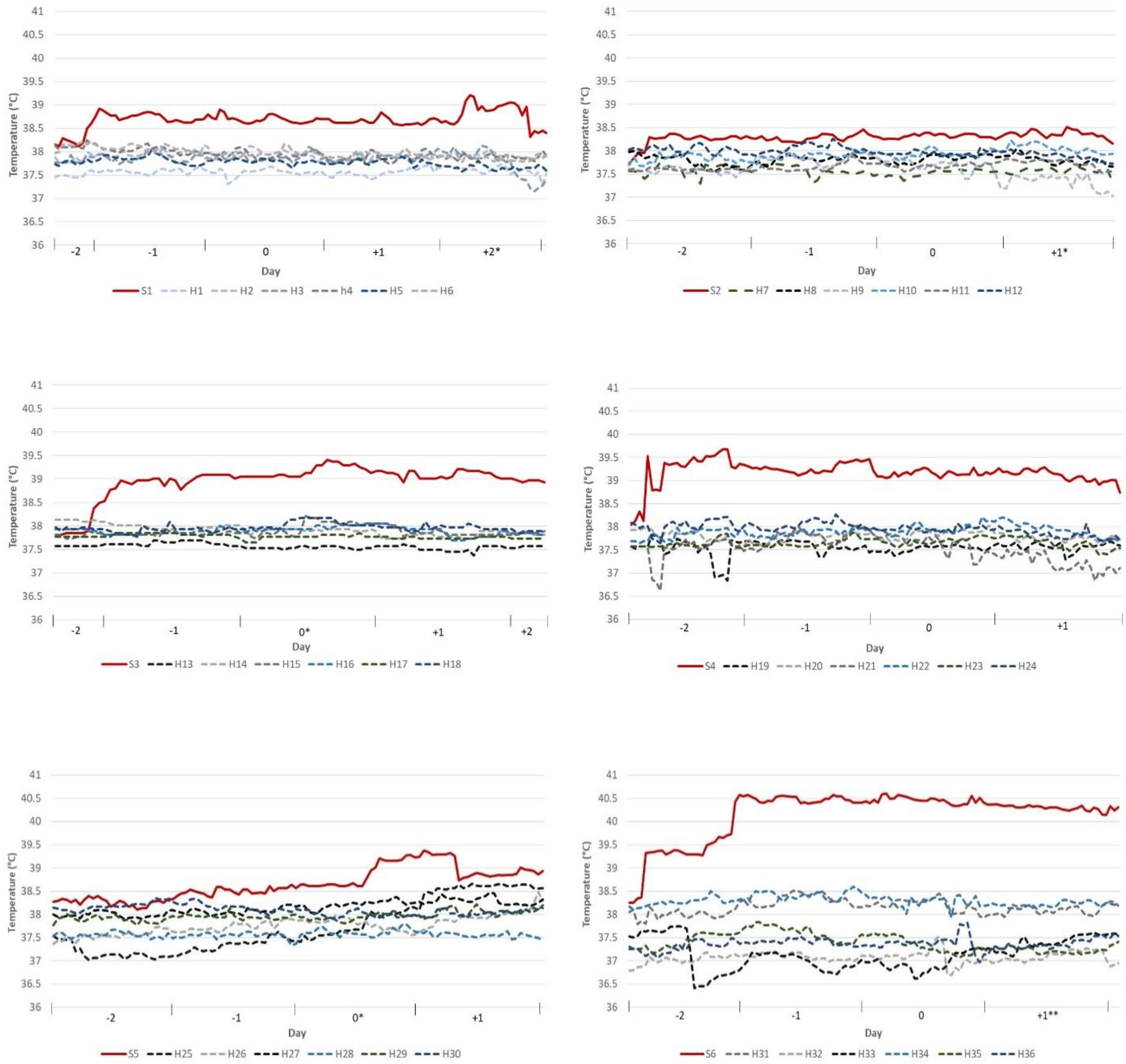

Fig. A1. Measurements of eye temperature (degrees Celsius) in "sick" and "healthy" animals before and after clinical symptoms were detected. Each graph represents one group with one sick pig (red continuous line and labelled as S) and six healthy pigs (discontinuous lines and labelled as H). "Day 0" 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.

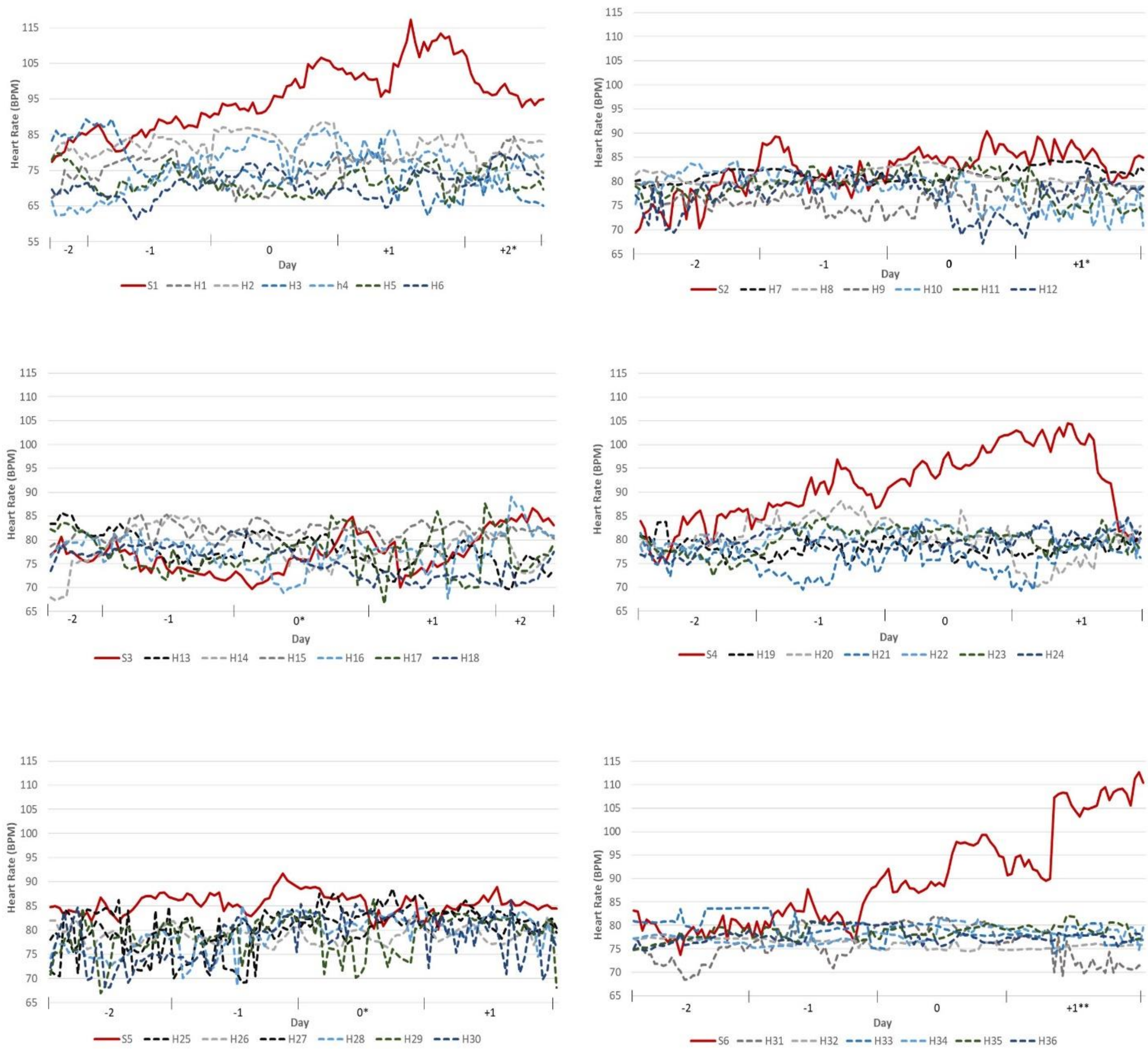

Fig. A2. Measurements of heart rate (beats per minute) in "sick" and "healthy" animals before and after clinical symptoms were detected. Each graph represents one group with one sick pig (red continuous line and labelled as S) and six healthy pigs (discontinuous lines and labelled as H). The symbol * indicates the day when antibiotic was administered via water, and ** indicates when a dose of injectable antibiotic was administrated to the sick pig.

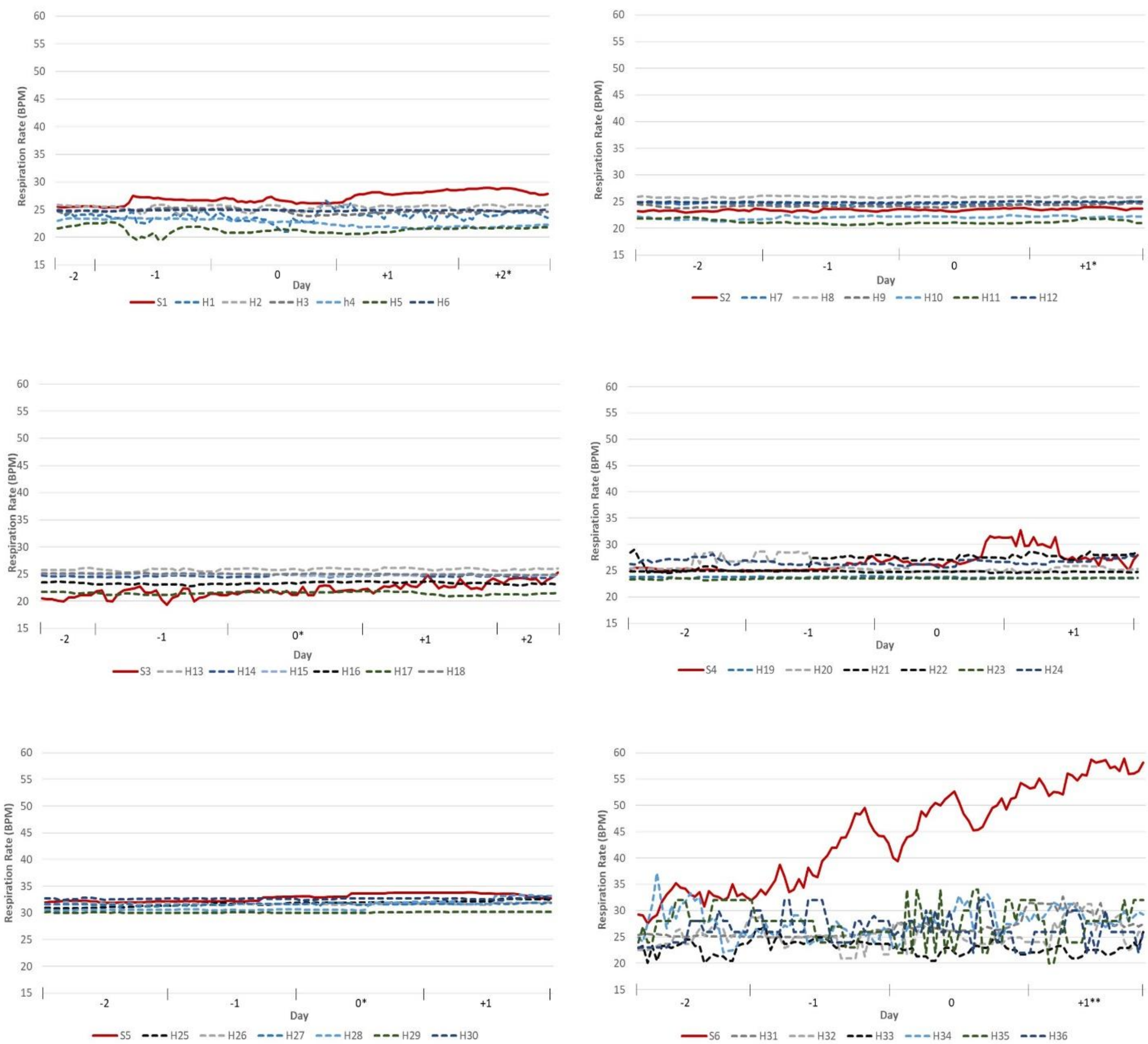

Fig. A3. Measurements of respiration rate (breaths per minute) in “sick” and “healthy” animals before and after clinical symptoms were detected. Each graph represents one group with one sick pig (red continuous line and labelled as S) and six healthy pigs (discontinuous lines and labelled as H). The symbol * indicates the day when antibiotic was administered via water, and ** indicates when a dose of injectable antibiotic was administrated to the sick pig.

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