Towards an automated method to monitor respiration rate for group-housed pigs by contactless video analysis

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Abstract

Respiration rate (RR) is an important physiological parameter highly related to heat stress and respiratory diseases in pigs. Contactless image/video-based RR monitoring has gained widespread interests as it is more animal friendly than traditional ways. However, recent studies mainly focused on monitoring RR for one animal, which is not the practical housing environment for pigs. The main challenge of RR monitoring for group-housed pigs is to detect pigs and select the Region of Interest (ROI) for each pig efficiently. The current study focuses on developing a computer vision-based approach to monitor the RR for group housed pigs towards an automatic way. The proposed method first detects each pig using an oriented bounding box that can capture the boundary between the pig and floor precisely without including many irrelevant pixels. Then the RR was extracted by analyzing the time-varying features extracted from the ROI. The method was validated on the video of four group-housed pigs wearing an ECG (electrocardiogram) belt to collect the gold standard (GS) RR measures. Forty video clips including both day and night occasions were selected to test the method. The comparison between RR obtained by the developed method and the gold standard showed good agreement: MAE, RMSE and correlation coefficient values of 2.38, 3.46 and 0.92, respectively, from four pigs with belts. Future work can further verify the method on the pig without wearing the belt to exclude the effect of the belt.

Keywords: physiological monitoring; oriented object detection; RGB video; animal welfare

Introduction

Respiration rate (RR) is an important physiological parameter for indicating the heat stress and respiratory diseases of pigs (Thi Thanh Thuy, 2005; Jorquera-Chavez et al., 2021). Conventional techniques to monitor RR for pigs usually require either flank movement observation by human (Brown-Brandl et al., 1998) or sensors (such as respiratory belt transducers, electrocardiogram morphology, and photoplethysmography morphology) in contact with the animal (Eigenberg et al., 2002). Such monitoring systems may be either labor-intensive for stockman or cause undesirable skin irritation and discomfort for animals. To this end, novel contactless monitoring approaches are increasing gaining attention these days. In addition, recent advancements in computer vision and camera technology have made images/videos available for measuring and monitoring RR of animals.

Regarding contactless-based RR monitoring systems for animals, only limited number of studies have attempted to measure the RR of pigs (Barbosa Pereira et al., 2019; Jorquera-Chavez et al., 2021). These studies used infrared thermal (IRT) cameras to capture the temperature changes related to breathing to extract RR from images/videos (Barbosa Pereira et al., 2019; Jorquera-Chavez et al., 2021). Even though using IRT camera is effective in RR monitoring, it could suffer from high cost, needs of specialized people, and sometimes of low signal-to-noise ratio. Compared to IRT camera, RGB (red, green and blue) camera are more convenient as it is low-cost and easy-to-use. In addition, previous studies only measured the RR for a single pig, and have not investigated with group-housed pigs, despite its practical relevance in housing environments for pigs.

The objective of this study is to develop a measuring system capable of monitoring RR in real-time for group housed pigs. The system aims to monitor the RR towards an automatic way by integrating computer-vision-based detection and signal analysis to extract RR with automated selection of ROI.

Materials and methods

Animal experiment and data collection

The experiment was conducted in the animal experiment facilities (TRANSfarm) at KU Leuven during late February and early March of 2022. The experiment protocol did not require formal ethical approval when judged by the Ethical Committee for Animal Experiment, KU Leuven., while it was approved as an activity (No. M016/2021). A total of 5 pigs (TN70 * PIC 408), at the age of 66 days, were included in the experiment. The pigs were group housed in one pen with a size of 2.90 m × 1.78 m (1.03 square meters per pig). A network camera (DH-SD1A203T-GN, Hangzhou, China) was located above the pen at the height of 2.5 m to capture the full pen area at a top-view angle (Figure 1a). The camera was turned on infrared mode on during nighttime (from 1900-0800 h). Video recordings of the animals were collected over day and night during the 21 experimental days. The frame rate of the recordings was 25 fps. The only controlled factor in the experiment was temperature, which was simulated based on Belgian's daily summer temperature profile. The lowest temperature was set to 16°C and the highest temperature was set to 25°C. Humidity was not manipulated in the experiment, being in the range 45-60% during the experiments, which is suitable for growing pigs according to the Temperature and Humidity Index (THI) for growing pigs in the study of Lallo et al. (2018).

In order to collect the Gold Standard (GS) for RR, four wearable belts (Zephyr BioHarness 3, Annapolis, Maryland, USA) containing ECG devices were put around the pig abdomen 5 cm lower than the position of the heart. The belt can record the RR of the animal every second with a range of 3 – 70 breaths per minute (bpm) and an accuracy of ±1 bpm. The animals were marked with numbers on the back using a livestock spray paint for indentification. Forty video sequences (Mean ± std: 2m24s ± 46s) were selected to test of the computer vision-based RR monitoring and 4pigs in each video were included in the test.

Respiration extraction

The workflow of extracting RR from video was illustrated in Figure 1. With the aim of automatically measuring RR over RGB videos, an object detection algorithm (Yi et al., 2021) was used to detect each pig first. The object detection algorithm was pre-trained to detect objects using an oriented bounding box for 40 epochs on the DOTA dataset (Xia et al., 2018) and 100 epochs on the HRSC2016 dataset (Liu et al., 2017). This pre-trained model was fine-tuned in this study using 123 frames from 40 video recordings, wherein every pig was labelled by an oriented bounding box via the labelImg labelling tool (https://github.com/chinakook/labelImg2). The training took about 30 minutes with 50 epochs and batch size of 4, which was measured on a single NVIDIA GeForce RTX 3090 GPU. Following the common practice of object detection, the training accuracy was evaluated by mean Average Precision (mAP), which was defined based on the Intersection over Union (IoU) method. Ten IoU thresholds (0.5 : 0.05 : 0.95) were used to evaluate the model and the model achieved 0.99 in mAP@0.5 and 0.87 in mAP @[0.5:0.95]. The fine-tuned model was then adopted to infer the location of pigs over the video recording with a speed of 11.62 fps. Figure 2 (a) shows a frame example illustrating the detection of individual pigs. To exclude large motion artefacts that usually appear around the head and tail, the middle third of the bounding box was further selected as ROI. Figure 2 (b) illustrates the automatic selection of ROI.

After each pig was detected, time-varying features were analyzed to estimate the RR. Specifically, In the selected ROI, the R, G and B intensity of each pixel were first summed up in each frame. Then each pixel series was detrended by Z-score normalization and the standard deviation (std) of each pixel was computed. The top 5% of pixel intensities with the highest std were selected as candidates. The mean value of the selected candidates was then computed and a ten-point moving average filter and bandpass filter with frequency range 0.25-2 Hz were applied to remove the noise. In order to compute the RR, the first derivative of the filtered signal was calculated, then all zero-crossing points in the first derivative signal were found out. The time between every two odd zero-crossing points was considered as the time for one inhale-exhale respiration cycle. Finally, the results were compared with the GS by performing Pearson correlation and using the Bland Altman method, and the comparison was performed based on a sliding window (60s) with a moving step (5s).

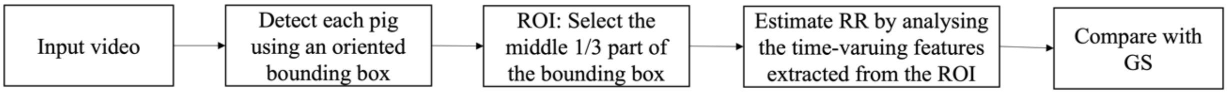


Figure 1: Flowchart illustrating the steps of extracting respiration rate from video.

Figure 2: Frame examples of: (a) detection result represented by the green bounding boxes; (b) automatically ROI selection represented by the red bounding boxes.

Table 1: Comparison of respiration rate extracted by computer vision (CV) versus the gold standard (GS) evaluated on 4 pigs.

Method	Range (bpm[1])	Mean	MAE (bpm[1])	RMSE (bpm[1])	Correlation Coefficient (r)
CV	(16.14, 65.60)	31.27	2.38	3.46	0.92***
GS	(13.60, 65.68)	31.38			

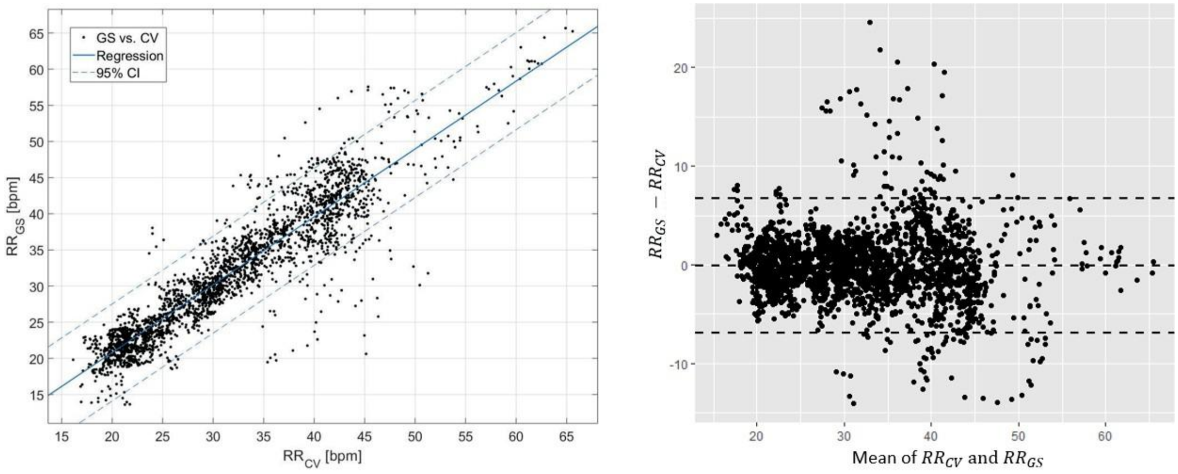
*** ($p < 0.001$)

[1] bpm: breaths per minute

Results and discussion

Table 1 shows the comparison between RR extracted by the developed computer vision (CV) method versus GS. The value of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) show low estimating error.

The correlation coefficient in Table 1 and regression result in Figure 3(a) show a strong correlation with the GS. Besides, the Bland Altman plot (Figure 2(b)) illustrates a good agreement between RR obtained from the CV and GS methods. For Figure 3(a) and (b), although there are some RR extractions outside the 95% confidence interval, the results still show very strong positive correlation and agreement between the GS and CV-based methods, which means the automatic ROI selection method can extract RR from RGB video.



(a) (b)

Figure 3: (a) regression analysis of the relationship between respiration rate (RR) obtained from gold-standard (GS) and computer vision (CV)-based methods (95% CI: 95% confidence interval; bpm: breaths per minute); (b) Bland Altman plot showing the difference between respiration rate (RR) obtained from gold standard (GS) and computer vision (CV)-based methods. The three dash lines represent the 95% confidence intervals and the mean of the difference between $RR_{!"}$ and $RR_{\#\$}$.

Figure 4: Frame examples illustrating the selected pixels for RR extraction.

The results shown in Table 1 and Figure 3 indicate the effectiveness of using the developed CV method to extract and monitor RR for group-housed pigs. While as mentioned above, the GS was obtained by the wearable belts. It might be a concern that the respiratory patterns are clearer around the belt. Figure 4 illustrated the selected top 5% percent pixels with higher std for RR extraction. It can be found that the pixels are mainly distributed around two regions: the belt and the edge between the abdomen and floor. However, to obtain the GS automatically, it cannot be avoided using the belt. Other approaches, e.g., observing the video and counting the fluctuations around the abdomen which was verified in the study of Jorquera-Chavez et al., (2021), could also be possible to obtain a reliable GS. In the experiment of this study, a pig not wearing the belt was also included. By observing the video, we found that the respiration rate for that pig was similar with other pigs. Thus in order to exclude the effect of the belt, future work can verify the CV-based method on that pig by obtaining the GS manually.

Conclusions

This paper presented a computer vision-based method to measure the respiration rate for group-housed pigs towards an automated way. The method consisted of an oriented object detector to automatically select the region of interest, followed by analysis of the time-varying features to extract respiration rate from this region. The comparison between respiration rate obtained by computer vision and the gold standard method showed strong agreement: MAE, RMSE and correlation coefficient values of 2.38, 3.46 and 0.92, respectively, from four pigs wearing belts. Based on the positive results from this study, future work can move forward to test the method on the pig without wearing the belt to exclude the effect of the belt.

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