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Monitoring sow postures, feeding and nursing activity using the combination of deep learning and image segmentation methods

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Abstract

Monitoring sow activity is valuable in moving towards more flexible housing during lactation as it strongly influences piglet survival. Detecting sows that are calm, do not suffer from health problems and nurse their litter efficiently is necessary to develop welfare-friendly systems. We developed procedures to automatically analyse sow activity including postures, feeding and nursing. The method was trained on nearly one million images collected from 10 sows over 5 days each. Sow activity was recorded using two RGB cameras to observe the sow from the front and from the back. Three convolutional neural networks (CNN) were developed for the top front view, the top rear view and for the two angles of view. They were combined so that the lack of consistency in prediction from the two single-view analyses triggered the third analysis. The sequential analysis of few successive images allows to confirm each detection. CNN were trained to identify eight main sow activities, with a mean precision of 85% for all traits. CNN were also coupled with an image segmentation based procedure to measure the intensity of nursing activity with distinction of pre and post massage from milk ejection.

Keywords: welfare, sow behaviour, image processing, deep learning, real-time

Introduction

For ethical, economical and societal reasons, it is necessary to reduce piglet mortality, especially when it depends on the sow, in connection with farrowing and lactation difficulties and if it results from the crushing of piglets by their mothers. In the future it would be beneficial, more profitable and more acceptable to the industry to produce sows that are able to rear more of their piglets to weaning. Guidelines limiting the use of strong restraint systems in pig farming are being adopted, but keeping sows blocked for several days around farrowing is still the only solution to limit losses by crushing in numerous populations. A Norwegian study evidenced that maternal behaviour has a genetic background (Vangen et al., 2005) that could be exploited in selective breeding to reduce piglet losses indirectly, for example by choosing sows that give easy access to the udder to their piglets. Being careful in their posture changes is also a desirable trait that would be worth to consider in selective breeding. Apart from a few ethological studies based on observer's video analyses (Baxter et al., 2012), it has never been recorded and measured.

Monitoring animals over a long time period enables to detect changes in activity level. With the fast evolution of sensor technologies, we can expect automatic collection of large amounts of various behavioural data. If accelerometers have been widely tested to record pig behaviour (e.g. Ringgenberg *et al.*, 2010; Matheson *et al.*, 2017), embedding the sensor on the animal is a main limitation to their general use. More sophisticated sensors may facilitate these kinds of behaviour measurements (Lao *et al.*, 2016, Dore *et al.*, 2020). Cameras raise increasing interest because they are non-invasive, and can be used to monitor several features, such as posture and water intake pattern. For example, sow postural activity in a crate can be estimated from images using a CNN with a very good accuracy (Nasirahmadi *et al.* 2019, Bonneau *et al.*, 2021), but also from unsupervised methods (Okinda *et al.* 2018). In this work, we study the potential of using two cameras, to monitor the main postures of the sows and milking detection. A group of lactating sows was video recorded, with two cameras positioned at the front and at the rear part of the crate. Video data were acquired over long periods of time, day and night. The set of image data extracted from the videos has been the subject of a detailed study to develop image processing techniques and artificial neural network. This article presents the methodology developed to determine, postural activity, including sow feeding activity. In addition, an image segmentation method was developed to measure sow nursing activity.

Material and methods

Monitoring Framework

Measurements were performed on lactating sows of the Large White breed, on an experimental farm. An artificial vision system was developed to carry out image acquisition. Ten sows were raised in crate from the entrance to the exist of the farrowing unit. Two IP cameras (Bascom model) have been installed to visualize the front and rear part of the sow. Cameras recorded at 10 Hz, regular RGB images from 6am to 6pm, and B&W acquired from infrared (IR) the rest of the time. The objective was to obtain, from the acquired videos, sow activity information on different acquired videos, during several days (night and day). Figure 1 below shows the two cameras used for one crate (a) and examples of night (b) and day (c) images acquired by the two cameras. For (b) and (c), the images from the front and rear camera are merged.

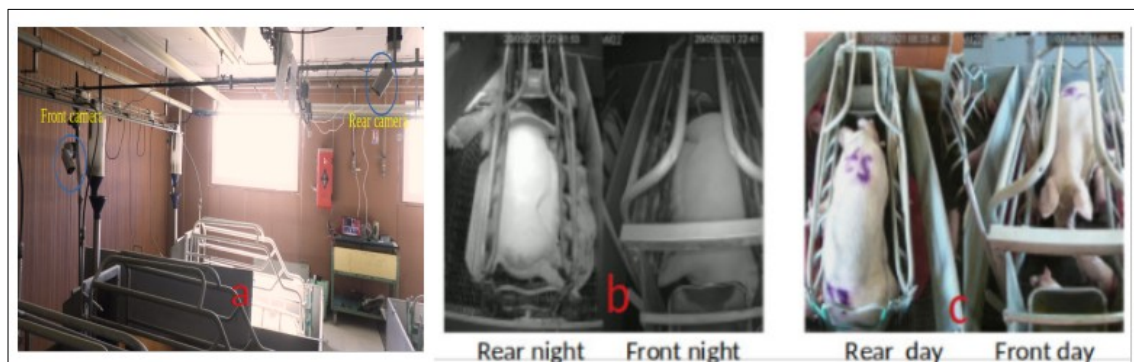


Figure 1: Vision device with two cameras fixed at the front and rear part of the crate, with night and day image visualisation

We were interested in the identification of ten main activities and postures of the sow: standing with and without feeding activity, sitting, lying sternally, nursing activities lying on the left or right sides, considering for each side, two possibilities (with and without piglet). Figure 2 presents images acquired with the two cameras, for the eight main sow activities. For each behavioral trait, the left and right images are respectively the images acquired with the rear and front cameras.



Figure 2. Images for the eight main sow activities under study, acquired from the rear camera (left side) and front camera (right side)

Posture detection

The study focused on a set of videos acquired and recorded for 50 days (10 sows over 5 days each). From these videos, an image-by-image scan was carried out to create the database of labelled images (Kabra et al., 2013), with the aim of subsequently train and evaluate some CNN to predict sow posture. The training image database included about one million images, for the 8 activities, divided into 3 groups: 330000 images from the rear camera, 330000 images from the front camera and 330000 images obtained by concatenating the images of the rear and front cameras. Three neural networks were developed for this study, using the python library Tensorflow. Several CNN architecture were tested, and Inception V3 was retrained, as it provided the best empirical results. The Inception V3 neural network model is a CNN developed by Google, which was trained on the basis of ImageNet images which includes millions of images and about 1000 categories, and which is composed of a training phase and a classification phase (Szegedy et al., 2015). The number of convolutional and fully connected layers is 48, in Inception V3 architecture. As the training phase has already been carried out, we are therefore only interested in the classification or data extraction phase (re-learning only of the last network layer), which is very fast and efficient. CNN were re-trained using transfer learning, by re-learning only the last layer of the network, which greatly speed-up the training process without dramatic loss of accuracy (30 minutes to create each of the three CNN).

Figure 3 presents the learning method general principle which includes a back propagation algorithm, in order to create a CNN, by minimizing errors inside the CNN layers, and the prediction task used for sow activity identification, for a given image. The three neural network trained independently were created from the image database for eight activities. From acquired images by the two cameras, a fusion data method (Figure 4) was used to obtain the final prediction result: if at least two CNN give the same prediction result, then the final prediction is this one, otherwise, if three prediction results are different then the sow activity is not determined.

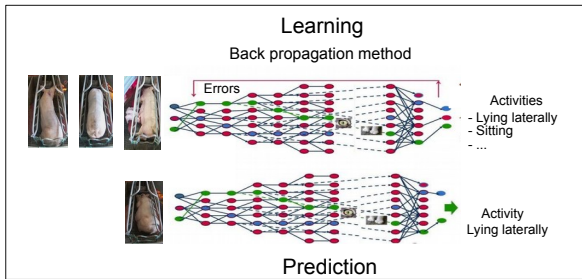


Figure 3. CNN development

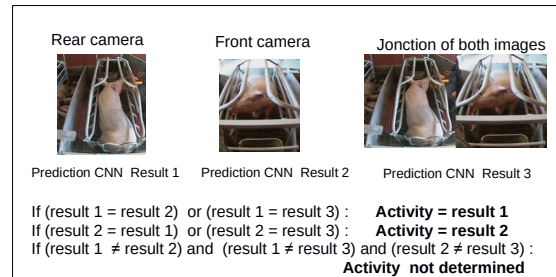


Figure 4. Fusion method for sow activity identification

Nursing Activity

When the sow is defined as lying on her side, when she is in one of two nursing situations (laying left with nursing or laying right with nursing), obtained during the first operation of the developed software, corresponding to sow activity identification, then a second operation, corresponding to the measurement of the nursing activity is launched. The image processing developed to carry out this operation consists in a first time to find automatically the rectangular area which contains the udder of the sow, in the rear image. For this, an artificial vision algorithm composed of image segmentation and mathematical morphology functions is used. Then the measurement algorithm is applied: it counts the number of points (pixels) that change of color intensity in the Red, Green and Blue color space, with defined thresholds for Red, Green and Blue components, in this area, between two successive images acquired at times t and $t + 0.1$ seconds. The intensity of nursing activity, is obtained by calculating the ratio between the number of points that change color and the rectangular area of the udder. The Figure 5 presents the rectangular area of sow udder and the points with a significant color change between two successive images (blue color), that characterize the nursing intensity.

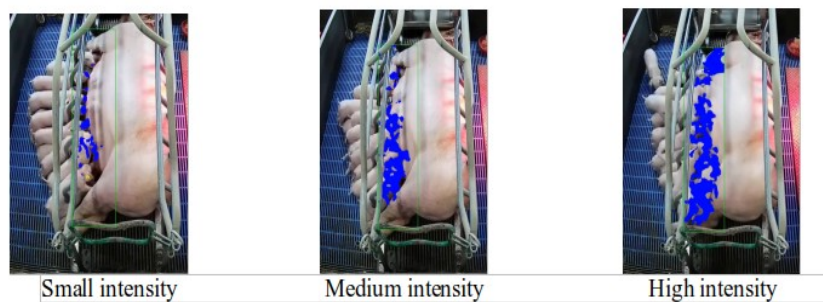


Figure 5. Illustration of nursing measurements detected from level of udder movement

Evaluation

On the big set data of acquired images (about 330000 images for rear camera, for front camera and for junction of both images), an image processing algorithm was applied in order to remove similar images, particularly for sternal, lying left or lying right activities (little movement of sows and the piglets). A dataset containing about 200000 images for each of the three image type, was obtained with this algorithm. From this dataset, a random set with about 150000 images for each of image type (rear, front and junction) was extracted for CNN development (training) and a second one with about 40000 images, for CNN testing and evaluation. For each activity, precision, sensitivity and f1-score values were computed to compare the three CNN and the fusion method, for the test images, with the following computations for each activity called p, from three confusion matrix data (True Positive (TP_p), False Positive (FP_p) and False Negative (FN_p)) obtained in the prediction results :

$$\text{Sensitivity}_p = \frac{TP_p}{TP_p + FN_p} \quad \text{Precision}_p = \frac{TP_p}{TP_p + FP_p} \quad f1\text{-score}_p = 100 \times \left(2 \times \frac{\text{Sensitivity}_p \times \text{Precision}_p}{\text{Sensitivity}_p + \text{Precision}_p} \right)$$

Results and Discussion

Table 1 presents the confusion matrix obtained for the eight activities with the three networks corresponding to individual CNN (rear camera (a), front camera (b) and junction of both images (c)) and with the fusion method (d), for analysing and comparing the three CNN performances, for sow activity prediction. The first column presents the eight activities, the second one presents the TP_p values, the others values in the matrix 8x8 are the FN values in horizontal lines and the FP values in vertical columns. FN_p and FP_p are the mean values for each activity p.

Table 1. Confusion matrix for eight activities for four methods (three individual neural networks and a fusion method)

Sternal	5422	138	8	59	309	210	278	146	Sternal	4756	135	20	63	1087	133	335	217
Sitting	14	3254	2	2	0	3	0	7	Sitting	58	3179	16	13	4	1	3	1
Standing feeding	0	1	2902	18	0	0	0	0	Standing feeding	5	18	2814	85	0	1	0	0
Standing not feeding	45	191	229	2923	4	11	3	4	Standing not feeding	57	382	388	2588	6	17	7	4
Lying right	115	0	0	1	589	181	24	3	Lying right	42	0	0	1	785	80	3	6
Lying right nursing	224	13	2	1	433	4815	30	61	Lying right nursing	203	14	3	5	1323	3828	49	1428
Lying left	110	3	0	4	159	134	2269	380	Lying left	44	2	0	0	18	8	2811	212
Lying left nursing	484	76	8	25	54	1545	677	8395	Lying left nursing	262	157	13	25	90	365	2295	8105
a									b								
Sternal	5384	223	10	86	512	235	268	66	Sternal	5462	419	2	47	527	93	188	90
Sitting	38	3191	5	46	0	0	0	1	Sitting	13	3260	4	3	0	1	0	1
Standing feeding	0	44	2803	70	0	4	0	2	Standing feeding	0	42	2849	32	0	0	0	0
Standing not feeding	19	218	262	2870	2	8	51	21	Standing not feeding	42	137	278	2980	1	6	11	3
Lying right	17	1	0	0	742	123	19	10	Lying right	36	1	0	0	768	105	6	4
Lying right nursing	152	20	2	6	1044	4304	156	1222	Lying right nursing	194	47	1	1	765	4615	17	1288
Lying left	32	3	0	0	48	32	2906	72	Lying left	29	5	0	1	27	26	2846	164
Lying left nursing	399	150	15	18	215	1374	2006	7116	Lying left nursing	325	257	14	11	57	930	1204	8574
c									d								

Table 2 presents the precision (P), sensitivity (S) and f1-score (F) values for the eight activities and the four prediction methods: CNN for Rear camera (CNN-R), CNN for Front camera (CNN-F), CNN for the TWO cameras (CNN-TWO) and Fusion Method (FM). Regarding the four methods, you can see, making a comparison between all the results, that the best results are obtained with the Fusion method, with high mean success rates for Sensitivity, Precision and F1-score equal to 85%. For the three individual CNN, the best results are obtained with CNN-R (84%). This CNN-R network (rear camera) can work alone to predict with accuracy, the sow activities. We can see that the best results are generally obtained for Sitting, and Standing activities (about 99%). For Laying left or right activities, without or with nursing, the result quality is variable, between 65% and 85%. Also, the activities such as Sternal and Lying left or right, without any piglets, can be difficult to discriminate. This point can be explained by the fact that it is difficult to annotate (expertise) these three activities, with accuracy, in the CNN training operation. If we take into account the sequential aspect of the measures in real time, in our software, improvements are done, for identification of these activities (Sternal and the four Lying activities). This principle permits to reduce false identification.

Table 2. Quality of four methods

	CNN-R Prediction result			CNN-F Prediction Result			CNN-TWO Prediction Result			FM Prediction Result		
	S	P	F	S	P	F	S	P	F	S	P	F
Sternal	0,83	0,76	0,79	0,71	0,83	0,76	0,79	0,88	0,84	0,83	0,87	0,83
Sitting	0,99	0,92	0,95	0,97	0,86	0,91	0,97	0,88	0,93	0,99	0,87	0,93
Standing feeding	0,99	0,93	0,96	0,96	0,89	0,92	0,96	0,92	0,94	0,97	0,92	0,95
Standing not feeding	0,86	0,98	0,91	0,75	0,94	0,84	0,83	0,94	0,88	0,86	0,98	0,92
Lying right	0,65	0,78	0,71	0,86	0,7	0,77	0,81	0,76	0,78	0,83	0,81	0,82
Lying right nursing	0,86	0,68	0,76	0,56	0,79	0,65	0,62	0,67	0,65	0,67	0,75	0,71
Lying left	0,74	0,85	0,79	0,91	0,77	0,84	0,94	0,77	0,85	0,92	0,86	0,89
Lying left nursing	0,75	0,82	0,78	0,72	0,69	0,7	0,63	0,73	0,68	0,75	0,75	0,75
MEAN RESULTS	0,83	0,84	0,83	0,80	0,81	0,80	0,82	0,82	0,82	0,85	0,85	0,85

The developed algorithm analyses the images acquired with the two cameras, identify the sow activity and record the results (the postural activity and the nursing intensity) into one file, with a frequency of 1 Hz, in live mode. Due to the absence of dedicated dataset, nursing activity was only evaluated by visual observations. This algorithm makes it possible to carry out detailed analyzes of the sow activity, to study their behavior over time and to carry out various comparisons between sows. Figure 6 presents the results obtained for one sow, during about 24 hours (86400 seconds).

The activity numbers between 1 and 8, are associated respectively to the following activities: Lying left, Lying left with nursing, Lying right, Lying right with nursing, Sternal, Sitting, Standing without feeding and Standing with feeding.

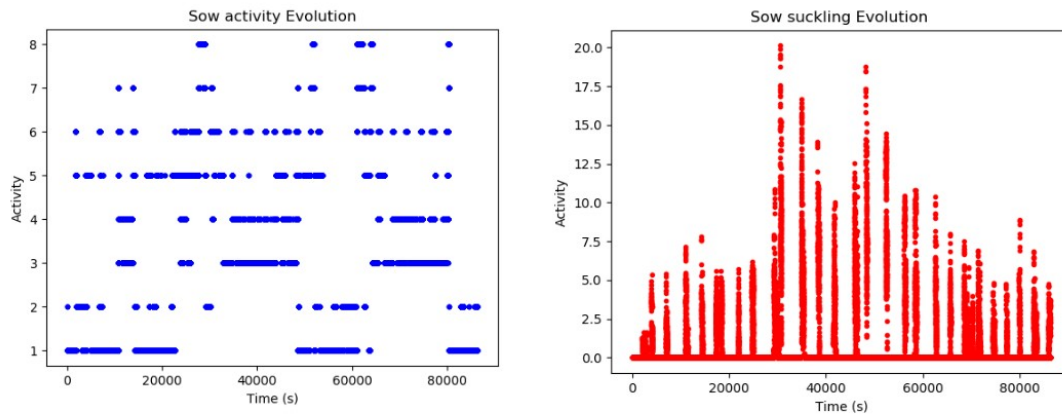


Figure 6: Results obtain during a long time (sow activity (blue) and nursing (red))

A detailed analyze of piglet nursing activities results obtained with the image segmentation algorithm, for several sows and for different time ranges (during day or night), showed that these results are similar to the nursing general activity, that we can see in many experimentation and tests of the piglet behavior: there are three main periods in one nursing activity. The first one is a first operation of piglets to obtain, to eject milk (a lot of movement of the udder (high intensity values)), the second one is the nursing (weak movement of udder (slow intensity values)) and the last one consists, like the first operation, to eject milk (big movement of the udder (high intensity values) to begin to prepare the next feeding (about one hour after) (Figure 7).

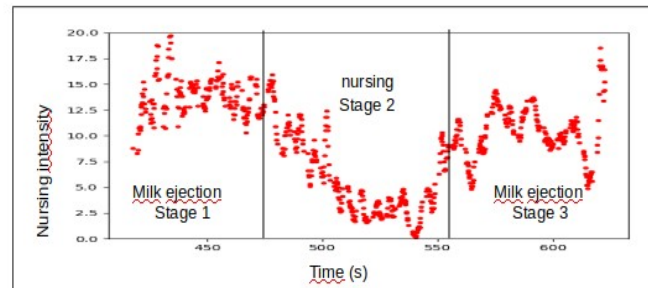


Figure 7: The three stages of piglet nursing activity – Artificial vision results

Conclusion

This paper proposed an artificial vision device constituted by two IP RGB cameras (with IR integrated sensor for night acquisition), connected to a computer, with the development of a real-time algorithm (working frequency of 1 Hz), for sow activities identification, using deep learning and image processing methods. The obtained result with the developed software permit to obtain data file which show the duration and the time range for the main activities, for long periods, night and day, including the measurement of feeding activities for sows and piglets (nursing activity). The image processing software can be used with only the rear camera or with the two cameras to increase the accuracy of prediction, for Sitting or Standing with feeding activities. To optimize the sow activity identification, sequential analysis of few successive images will be tested to allow to confirm each identification, and so to improve the activities identification, for Sternal and Lying activities.

The measures obtained permit to finely analyse the activity pattern of sows over long periods of time, to define variations over time for each sow and to compare different sows, in order to identify, in particular, the individuals which present a deviant profile by comparing them to those which have a normal profile. The developed device will be installed in different pig farms in order to test and validate the developed software, with the objective to see if the complete device including the two cameras and the developed software is able to operate in various environments, with different floor colours, various barrier positions, and also modifying the position and orientation of the two cameras. In order to improve the software, new images acquired in various pig farms will be annotated to enrich the training image database, and updating the neural networks. This type of method used for sow farms, using video devices to take measurements, will be tested for other animals such as sheep, cattle and goats.

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