Posture identification for stall-housed sows using convolutional neural network

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Abstract

Research has shown that posture records can be used to assess the health, welfare, and estrus status of sows and gilts which are critical for the commercial swine industry. Individual animals can be monitored in real-time using imagery sensors and accelerometers to quantify their behavior patterns in a large herd. In this study, a rear-view robotic imaging system, consisting of a LiDAR camera, edge-computing unit, and robotic platform, was developed to monitor the behavior of sows/gilts housed in gestation stalls. Collected images were used to classify the four types of postures, i.e., STA: standing, SIT: sitting, SL: sternal lying, and LL: lateral lying, using convolutional neural networks (CNNs). In this study, eight sows were continuously monitored at a 5-minute interval for 30 days. All sows were managed and their estrus checks were conducted according to standard farm operation protocols. Performance between four CNN models (VGG16, MobileNet, Xception, and DenseNet121) was compared. Results show VGG16 had significantly lower validation accuracy (99.8%, $p<0.05$) compared to MobileNet, Xception, and Densnet121 (99.91% ± 0.04%). The Xception model yielded significantly higher test accuracy (98.25%). The MobileNet model required significantly less time to process each image (t = 210ms). Daily activity level (calculated as the portion of STA and SIT postures) and semi-idle level (calculated as the portion of SL posture) on the day of onset of estrus were significantly higher than those on the previous days. Daily idle level (the portion of LL posture) decreased significantly on the day of the onset of estrus. In addition, the absolute change of daily idle level was significantly higher than that of daily activity and semi-idle level ($p<0.05$), suggesting that daily idle level could be a more reliable indicator than daily activity level for identifying the onset of estrus events. In this research, no distinct behavior pattern was observed around the expected return estrus. The study concluded that posture patterns derived from the robotic imaging system could help detect sows' first onset of estrus but might not help detect return estrus.

Keywords: swine reproduction; estrus detection; robotic imaging system; 3D camera; digital agriculture

Introduction

Pork production in the U.S. in 2021 supported over 610,000 jobs, provided $35.86 billion of personal income, and generated $57.2 billion of gross revenue (NPPC, 2022). Current management practices in swine production require skilled workers to spend extended hours in a hazardous environment to interact with animals, which can not only diminish worker's mental and physical health but also introduce additional biosecurity risks to the animals (Rimac et al., 2010; Viegas et al., 2013). The harsh working environment makes it difficult to hire local workers. Several states showed signs of difficulties in hiring reliable employees to work in swine farms from the local labour market and the turnover rate among these animal caretakers in swine farms in the U.S. was reported to be between 20 and 35% (Black and Arruda, 2021). On-farm employee turnover is costly and may hinder productivity. As the labour shortage in swine farming is expected to grow continuously (Boessen et al., 2018), there is an urgent need to use emerging technologies to reduce labour demands and intensity and improve management efficiency in swine production.

For decades, the Back-pressure test (BPT) method has been the most common on-farm practice for estrus detection (Kraeling and Webel, 2015). Breeding technicians apply pressure on sow's back to mimic the mounting behavior of a boar, and the sow will be determined as onset of estrus if it is immobile in response to the test (Ostersen et al., 2010). This current practice for estrus detection in sows makes up for 30% of total labour input for commercial breeding facilities (Freson et al., 1998). With the large sum of labour required for estrus detection, the current average farrowing rate in the U.S. was 82% in 2021 (PigChamp, 2022), which is lower than the commonly accepted target of 85% (Gadea et al., 2004).

In efforts to improve the accuracy and reduce the required labour for estrus detection, different approaches for capturing the biological and behavioural traits around the onset of estrus events were tested. For instance, studies showed that the increase in ear and vaginal temperature before the onset of estrus events can be captured by attaching thermometers in the region of interest (Geers et al., 1995; Simões et al., 2014). Vulvar swollenness can be captured using a LiDAR camera which could be used as an indicator for the onset of estrus events (Xu et al., 2023). In addition, a study reported 81.6% specificity for estrus recognition by attaching an accelerometer to the sow's neck and quantifying the change in standing and mounting behavior (Wang et al., 2020). Another study was able to identify 87.4% of the onset of estrus events by monitoring the frequency and duration of individual sow's visit to a boar using a radio frequency identification detection (RFID) sensor (Cornou, 2006).

Although the increase in activity is one of the symptoms of estrus events, activity level is subject to the animal's health status, such as lameness, body weight, and well-being (Grégoire et al., 2013; Young and Aherne, 2005). The increase in activity level implies that a sow may also have less time in a state of inactivity (idle status), which is commonly referred to as a sow with laterally lying posture (Nicolaisen et al., 2019). Therefore, the decrease in idle level may be a more reliable indicator than activity level for estrus detection. Furthermore, most studies for posture recognition of sows housed in individual crates using images captured from the top view (Kasani et al., 2021; Lao et al., 2016). However, rear-view 3D images captured with LiDAR camera have the potential to help identify vulvar swollenness and evaluate structural correctness of sows, which may provide more insight to help understand the sow's condition. Therefore, the objectives of this research included: (1) to compare the performance of different deep learning models in identifying sow's posture (standing, sitting, lateral lying, sternal lying) using different types of images, (2) to study the posture patterns of sows around the onset of estrus and return estrus.

Materials and methods

Experimental data

This study was conducted at the Swine Teaching and Research Farm of the University of Missouri from March 15 to April 17, 2022. The facility has 12 gestation stalls with a fully slatted floor. A robotic image system equipped with a LiDAR camera (L515, Intel RealSense, Santa Clara, CA, USA) was built to collect rear-view images of each sow at a 5-minute interval. The LiDAR camera collected three types of images, i.e., infrared (IR) images (640×480 pixels), red-green-blue (RGB) images (1280×720 pixels), and depth images (Depth accuracy < 5 mm within a 1-m distance). Both IR and RGB images were aligned to the depth image frames pixel by pixel using a Python library Pyrealsense2 (RealSense SDK 2.0, Intel, Santa Clara, CA, USA). Depth images were collected in two formats, i.e., (1) Depth Images (DI), where each pixel value represented the distance between the object and the camera's planar surface, and (2) Depth Map (DM), a 640×480×3 matrix including 3-dimensional (3D) information (X, Y axes and Z depth). The images were saved in the corresponding folder based on the image type and named with the sows' ID number and imaging time. In this study, a total of 21 gilts or multiparous sows were used for data collection. The first group consisted of 12 sows, and the second group consisted of 9 sows. Eight sows in the second group were weaned between March 20 to 22, 2022, and were moved to the individual breeding stalls equipped with the robotic imaging system. All sows were managed using standard operation protocols of the farm. Estrus check was performed by a breeding technician once per day in the morning using the back pressure test with the presence of a fence line boar after 2 days of weaning. No artificial insemination or natural breeding was given upon detection of the onset of estrus. Return estrus was not checked. Fence line boar exposure was not provided around the returned estrus. The expected date of returned estrus was marked on the 21 days after the onset of the first estrus.

Posture recognition models

Six types of images were tested for posture recognition (Figure 1). Imagery data DI was converted from 16-bit unsigned integer format to 8-bit unsigned integer format. DI_3 was acquired by applying colormap to the original DI image. The 3-channel DI_3 images were stacked with the corresponding IR images (as alpha channel) to make RGBA images, which were then converted to 3-channel RGB values using Python Pillow (Version 9.1.1). DM image was acquired by converting absolute values of DM to 8-bit unsigned integers. DM_IR was acquired by stacking the DM image with the corresponding IR image and convert into 3-channel RGB values.

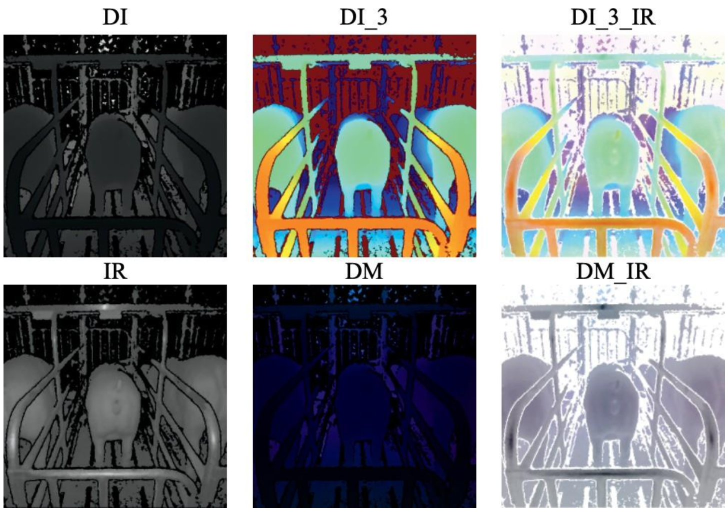

Figure 1: Examples of preprocessed images. DI = depth images; DI_3 = coloured depth images; DI_3_IR=colored depth images with infrared image as alpha channel; IR = Infrared images; DM = depth map; DM_IR = depth map with infrared image as alpha channel.

In this study, a total of 4,800 IR images (4 postures × 100 images/sow × 12 sows) from the first group of sows were manually labelled into four postures, i.e., Standing (STA), Sitting (SIT), Lateral lying (LL), and Sternal lying (SL). The definition of each posture and example of a labelled IR image for each category is shown in Figure 2. From the labelled IR images, the other 5 image types (DI, DM, etc.) were labelled accordingly. Each type of image dataset was split into 80% training and 20% validation. Four pre-trained (based on ImageNet) deep learning architectures (*VGG16*, *MobileNet*, *Xception*, and *DenseNet121*) were used to recognize the sow's posture. The posture recognition models were implemented in Google Colaboratory (Colab, Alphabet Inc, CA, USA). The trained models were tested using the data collected from 9 sows in the second group. The testing dataset consists of 2,297 images collected by the robotic imaging system from the 9 unseen sows in one day. The models' performance was evaluated using classification accuracy and F1 scores. In addition, the trained models were also loaded in a Raspberry Pi 4B (4GB, Cambridge, UK) and the processing time was measured in milliseconds for 500 images. Comparison between image types and model types on model performance was performed using TukeyHSD (RStudio 1.2.5033).

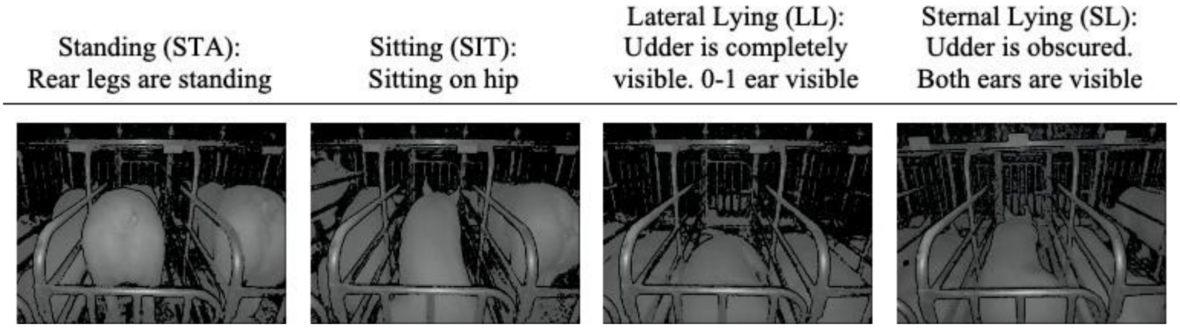

Figure 2: Illustration of the four defined postures based on IR images.

The IR images of the eight weaned sows were classified into corresponding postures using the trained *Xception* model. Four posture classes were assigned into 3 behavioural categories (Activity: standing and sitting; Idle: lateral lying; Semi-Idle: sternal lying). Behavioural level (i.e., activity level, idle level, semi-idle level) was defined as the percentage of each behavioural type in a 24-hour window observation calculated at every hour (lagged rolling average window), which was used to assess potential differences in the behavioural patterns. Daily behavioural level (24-hour) of each behavioural type refers to the behavioural level evaluated at 12 PM (noon).

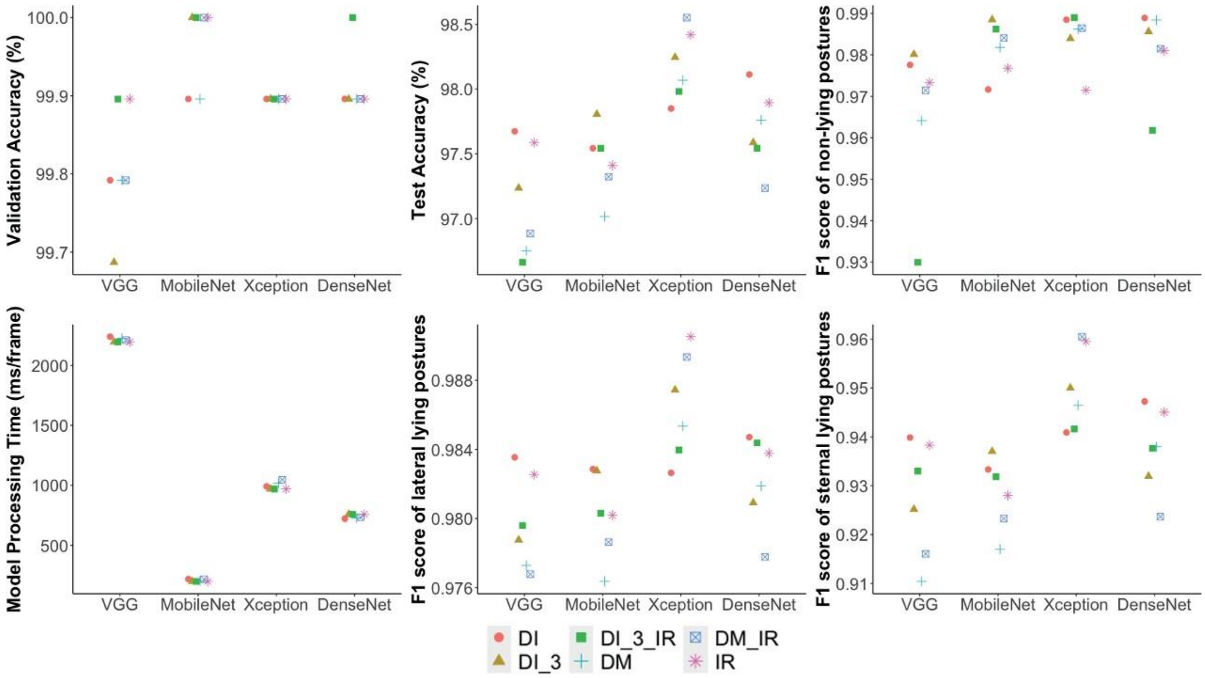

Figure 3: Posture recognition models' performance with different input image types

Results and discussion

Posture recognition model evaluation

The comparison of validation accuracy, test accuracy, F1 score for different behaviors, and the run time for each image type between different models are shown in Figure 3. According to the TukeyHSD test, there was no significant difference in model performances when using different types of input images for posture recognition. Results show that the VGG16 took significantly more time ($p<0.01$) than the rest of the models to process each image and yielded significantly lower validation and test accuracy ($p<0.01$). Meanwhile, the MobileNet took significantly less time ($p<0.01$) than the rest models to process each image, and no significant difference in performance for recognizing standing and sitting postures compared to the rest of the models ($p>0.1$). Although the Xception model took more time ($p<0.01$) to process each image frame than MobileNet and DenseNet, it had significantly higher test accuracy and F1 scores for lateral lying and sternal lying postures ($p<0.05$). The overall performance of DenseNet was between MobileNet and Xception. Although DenseNet took more time to process each image compare to MobileNet, no significant improvement in test accuracy or F1 scores for different posture classes was observed.

Based on the performance between different models shown in Figure 3, among the models tested in this study, MobileNet should be used when needing to monitor sow's activity level at a high frame rate (i.e., video feed), and Xception should be selected when need to accurately distinguish different lying postures (sternal and lateral).

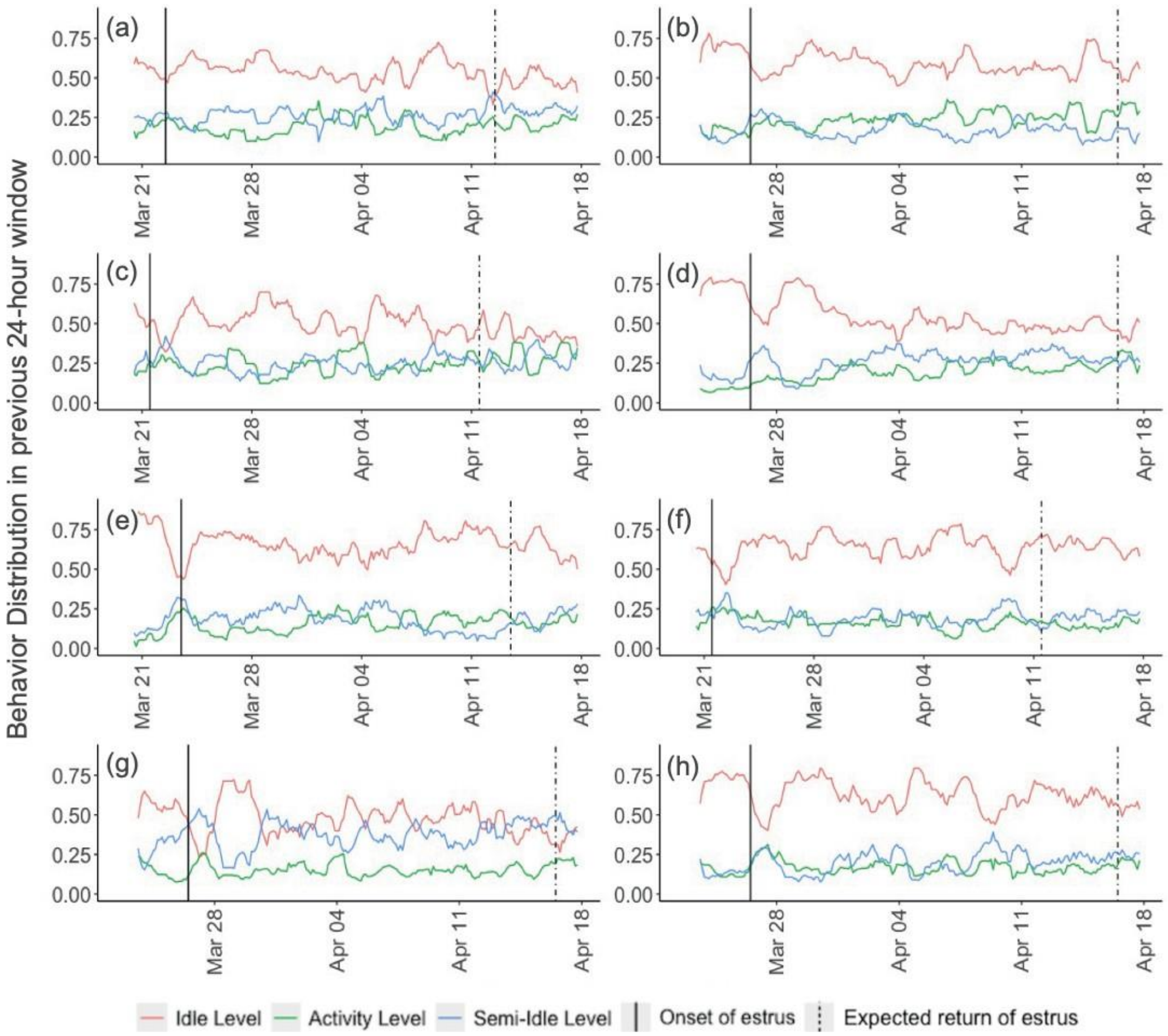

Figure 4: Behavior levels of individual sow after weaning.

Behavior patterns of sows

Behaviour patterns (i.e., activity level, idle level, semi-idle level) of the eight sows in the entire experiment period are shown in Figure 4. The average activity, idle, and semi-idle levels in the entire experiment period were 18.6±3.6%, 57.5±6.8%, and 23.7±6.67%. All of the eight sows showed declined idle level before the onset of estrus approached. Two of the 8 sows (Figure 4a, e) had the onset of estrus when idle level reached local minimum values. Only one of the eight sows showed no noticeable increase in semi-idle level (Figure 4a). In general, around the onset of estrus, the increase in activity level is less distinguishable compare to semi-idle level. Only 3 sows (Figure 4e, g, h) showed a distinct increase in activity level prior to the onset of estrus. No distinct pattern in behavior record was observed around the expected return estrus.

To show the changes in daily behavior patterns as sows approaching estrus, the average daily activity, idle, and semi-idle levels evaluated at 12 PM, and their corresponding increases compared to the previous day are shown in Figure 5. Daily idle level started to decrease and daily semi-idle level started to increase one day prior to the onset of estrus event, but daily activity level only started to increase on the day of onset of estrus event (Figure 5a). One day after the onset of estrus, daily idle level increased, and both daily activity level and semi-idle level decreased. As illustrated in Figure 5b, the largest decrease in daily idle level and the largest increase in daily activity and semi-idle level occurred on the day of onset of estrus. On the day of onset of estrus, not all sows showed a positive increase in daily activity and semi-idle level. However, all sows showed decreases in daily idle level, and the magnitude of the change in daily idle level was significantly higher than the change in daily activity and semi-idle level ($p<0.05$).

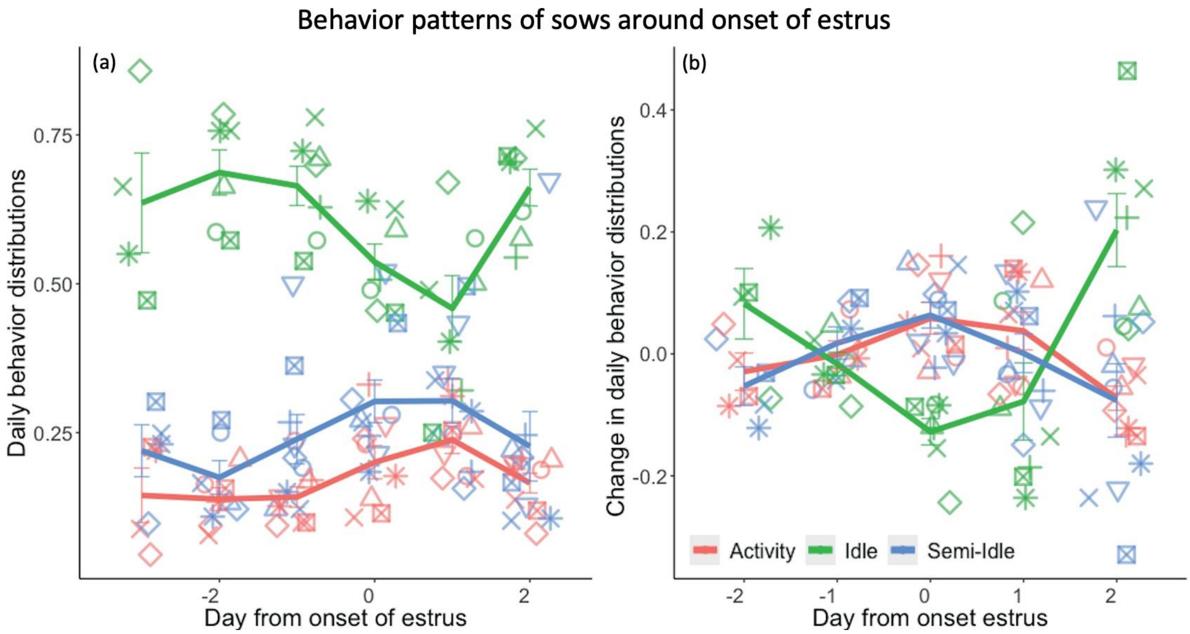

Figure 5: Behavior patterns of sows around onset of estrus events (shape of points represent individual sow).

Lateral lying sows are often considered in a state of total relaxation (i.e., sleeping), whereas sternal lying sows are often awake and alert to their surroundings (Nicolaisen et al., 2019). Sows tend to seek and interact with a boar as estrus approaches (Cornou, 2006), and the increasing interest in the surroundings may be the reason for increased activity and semi-idle level and the decrease in idle level around onset of estrus. As a result, these behavior records of sows can be potentially used for detecting onset of estrus. However, no distinct behavior pattern was observed around the expected return estrus. One potential explanation is that as sows regain body weight after weaning, they have more strength that allows them to react to the surroundings changes (i.e., nearby noise, adjacent sow's movement), and therefore makes it harder to identify behavior patterns around the expected return estrus.

Conclusions

This study evaluated the performance of different convolutional neural network models in identifying sow's posture. Result indicated that the image type has no significant impact on the posture recognition models' performance. Xception has the best accuracy but requires a longer processing time than MobileNet and DenseNet121. Using the posture recognition model to monitor individual sow's behavior patterns after weaning, result indicated significant increase in daily activity and semi-idle level, and a significant decrease in daily idle level was found on the day of onset of estrus. No distinct behavior pattern was observed around the expected return estrus. The study suggests that sow's behavior pattern may be used to help detect onset of estrus, but may not be useful for identifying return estrus.

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