Automatic recognition of lactating sow behaviors through depth image processing

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Keywords
Animal welfare, Depth image, Image processing, Sow behaviors

Disciplines
Agriculture | Bioresource and Agricultural Engineering

Comments

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Abstract

Manual observation and classification of animal behaviors is laborious, time-consuming, and of limited ability to process large amount of data. A computer vision-based system was developed that automatically recognizes sow behaviors (lying, sitting, standing, kneeling, feeding, drinking, and shifting) in farrowing crate. The system consisted of a low-cost 3D camera that simultaneously acquires digital and depth images and a software program that detects and identifies the sow's behaviors. This paper describes the computational algorithm for the analysis of depth images and presents its performance in recognizing the sow's behaviors as compared to manual recognition. The images were acquired at 6 s intervals on three days of a 21-day lactation period. Based on analysis of the 6 s interval images, the algorithm had the following accuracy of behavioral classification: 99.9% in lying, 96.4% in sitting, 99.2% in standing, 78.1% in kneeling, 97.4% in feeding, 92.7% in drinking, and 63.9% in transitioning between behaviors. The lower classification accuracy for the transitioning category presumably stemmed from insufficient frequency of the image acquisition which can be readily improved. Hence the reported system provides an effective way to automatically process and classify the sow's behavioral images. This tool is conducive to investigating behavioral responses and time budget of lactating sows and their litters to farrowing crate designs and management practices.

1. Introduction

Animal behaviors are reflective of its welfare/well-being state. They contain important information that can enable producers to better manage livestock (Brown-Brandl et al., 2013). For instance, research has shown that changes in feeding behavior can occur in response to thermal conditions of growing–finishing swine (Nienaber and Hahn, 2000), health status of sow and feedlot cattle (Cornou et al., 2008; Griffin, 2001), and diet of dairy goats (Adijaoude et al., 2000). Drinking behavior of pigs can be indicative of disease outbreak such as intestinal disorders (Kashiha et al., 2013; Madsen and Kristensen, 2005) and indoor climatic conditions (Bird and Crabtree, 2000). Lying or moving behaviors of lactating sows influence the livability of piglets (Mainau et al., 2009; Valros et al., 2006). Activity levels indicate the health and welfare of broiler chickens (Aydin et al., 2010); and they may also be used as an index of the thermal comfort for pigs (Andersen et al., 2008).

Traditional manual observation of real-time or recorded animal behaviors is laborious, subjective, inefficient, expensive, limited in the amount of data, and prone to human errors. Many sensors and sensing techniques are available or under development to increase the ability of automating measurements of animal behavioral and biological responses. Nowadays, image analysis (Ahrendt et al., 2011), sound analysis (Guarino et al., 2008) and other electronic sensors such as RFID (Brown-Brandl et al., 2013) are increasingly finding their use in animal production.

Digital image analysis is a common method used to automatically monitor animal behaviors and welfare (Shao and Xin, 2008; Kristensen and Cornou, 2011; Lao et al., 2012). It focuses on the animal's horizontal distribution attributes. Analysis of digital images obtained from video-recordings is an effective tool for studying livestock behaviors under various environmental conditions (Porto et al., 2013). During digital image processing, image segmentation and feature extraction are the most important steps.
among the image analysis methods considered. Digital image analysis methods can work well under the following conditions: the animal images have a high contrast with the background to allow for image segmentation; the background is constant or has constant brightness variations to extract the animal features from the image; the color range applied to the animal is different from the background (Porto et al., 2013). However, image segmentation in digital RGB image can be problematic under real farm conditions due to dynamic background restrictions, such as dim or uneven light intensity of the house and varying floor status. These factors can affect the robustness of the algorithm for accurate classification.

To improve the ability of attending farrowing and piglet livability, Cornou and Kristensen (2014) researched a method to monitor sow’s activity before, during, and after farrowing through analysis of recorded video. By means of image processing, Viazzi et al. (2014) and Bahr and Berckmans (2014) developed continuous automated detection of aggressive interactions among pigs and achieved an 89% detection accuracy. Applying a multi-process Kalman filter, Cornou and Lundbye-Christensen (2010) reported a 64% average recognition rate for passive (lying laterally or sternally) and active (feeding, rooting, and walking) behaviors of sows. Escalante et al. (2013) employed a supervised machine learning approach to classify sow activities recorded with accelerometers and achieved an average recognition rate of 74.6%. Oczak et al. (2015) used accelerometer data to classify nest-building behaviors of non-crated farrowing sows and obtained 86% accuracy.

Information captured by a depth image sensor differs considerably from that of color digital images in that each pixel in the depth data reflects the distance between the object and the depth image sensor. Depth image analysis is a new method that helps detecting data from that of color digital images in that each pixel in the depth image data need to be processed first, which included the following steps (b) to (f) below to obtain the necessary feature values for identification of the sow’s behaviors.

a. The Kinect sensor returned 16-bit raw depth frame data, with the first 3 bits representing the identification of the object and the remaining upper 13 bits providing the measured distance between the subject pixel and the Kinect sensor in mm (Jana, 2012). To change the raw depth data to real (physical) depth data, i.e., distance between each point of the sow and the floor, a 3-bit shift operation (i.e., dividing the 16-bit value by 8) was performed, followed by subtraction, as shown in Eqs. (1) and (2). The new depth data were further processed following steps (b) to (f) below to obtain the necessary feature values for identification of the sow’s behaviors.

$$height_{output} (cm) = \frac{1}{8} \times \text{(raw depth data)} \times \frac{1 \text{ cm}}{10 \text{ mm}}$$  \hspace{1cm} (1)

$$\text{New depth data} (cm) = height_{inner} - height_{output}$$  \hspace{1cm} (2)

where \(height_{inner}\) is the height of the kinect camera above the floor in cm.

Note that the raw depth data were in mm, while the new depth data were in cm.

b. Set high (>90 cm) and low (<6 cm) threshold values and four sides of the farrowing crates to 0 to reduce noise effect and speed up the processing.

c. Remove the feeder and crate frame pipes, then reconstruct the sow areas blocked by the pipes through line refilling.

d. Apply moving average filter to fill the small holes in the depth image of the sow to obtain a clear version of the sow’s depth image.

e. Change the depth image to a binary image to extract certain important features, including the sow’s centroid coordinates \((X_{centroid}, Y_{centroid})\), leftmost and rightmost pixels as the head
pixel and hip pixel, respectively; then calculate the $x$-coordinate of midpoint pixels between the head and the centroid, between the centroid and the rear to yield four $x$-coordinates – $x_{\text{head}}$, $x_{\text{hip}}$, $x_{\text{shoulder}}$, and $x_{\text{loin}}$, respectively.

f. Divide the sow in the depth image into 7 parts (all, upper half, lower half, head, shoulder, loin and hip), as shown in Fig. 2. A horizontal line $y = y_{\text{centroid}}$ passing through the sow’s centroid was drawn to divide the upper and lower parts of the sow, and the other four parts were divided by three vertical lines of $x = x_{\text{shoulder}}$, $x = x_{\text{centroid}}$, and $x = x_{\text{hip}}$.

g. Calculate the average value of all the depth pixels of each sow’s part, designated as $d_{\text{all}}$, $d_{\text{upper}}$, $d_{\text{lower}}$, $d_{\text{head}}$, $d_{\text{shoulder}}$, $d_{\text{loin}}$, and $d_{\text{hip}}$, respectively.

### 2.2.2. Definition of the sow behaviors

The sow’s behaviors covered in this analysis included lying, sitting, standing, kneeling, feeding, drinking, transitioning or shifting from one behavior to another, and moving. The definitions and description of the behaviors (Beirendonck et al., 2014; Johnson et al., 2001) are listed in Table 1.

### 2.2.3. Sow behaviors recognition algorithm

The sow behaviors recognition algorithm included four parts (Fig. 3). Part 1 processes depth image and obtains important feature values as previously described. Part 2 recognizes the sow behaviors (lying, sitting, kneeling, standing, feeding, and drinking) in the current image. Part 3 recognizes changes in the sow’s behaviors between the current image and the previous image, i.e., moving and shifting. Part 4 saves the algorithm results, including saving classification to the database (using Mysql database), the processed depth image, and the corresponding digital image to a new image, which makes the subsequent manual recognition/validation more convenient.

Part 2 involves the following steps to recognize the sow’s behaviors automatically. It should be noted that values $V_1$ to $V_9$ used in the algorithm will vary slightly with the camera’s height and resolution, the nipple drinker’s position and height, and the feeder’s position and size. In this paper, these values were acquired by statistical analysis of half-day worth of processed depth images, and are defined as follows.

![Fig. 1. Example of (a) digital image and (b) raw depth image of a lactating sow and litter in a farrowing crate.](image)

![Fig. 2. Definitions of seven parts of the sow in the depth image: (a) all, (b) upper and lower half, and (c) head, shoulder, loin, and hip; and x and y coordinates for the positions.](image)

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### Table 1 Definition and description of sow behaviors in a farrowing crate.

<table>
<thead>
<tr>
<th>Definition</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lying$^a$</td>
<td>Resting with her side in contact with the farrowing crate floor. In this study lying was further divided as either her backside facing the heat lamp (“backside facing heat lamp”) or her udders facing the heat lamp (“udders facing heat lamp”)</td>
</tr>
<tr>
<td>Sitting$^a$</td>
<td>Sitting on her hip. Two types: sitting only, and sitting and drinking</td>
</tr>
<tr>
<td>Standing$^a$</td>
<td>Standing still or walking. Three types: exploring, standing and feeding, and standing and drinking</td>
</tr>
<tr>
<td>Kneeling$^a$</td>
<td>The front legs are kneeling on the floor and the behind legs are standing</td>
</tr>
<tr>
<td>Feeding$^b$</td>
<td>Head in the feeder with up and down movement</td>
</tr>
<tr>
<td>Drinking$^b$</td>
<td>Mouth on nipple drinker</td>
</tr>
<tr>
<td>Moving$^c$</td>
<td>The Eulerian distance of the sow’s centroid between two consecutive depth images</td>
</tr>
<tr>
<td>Shifting$^c$</td>
<td>Transitioning from one behavior to another</td>
</tr>
</tbody>
</table>

$^a$ Behaviors that occur exclusively.

$^b$ Behaviors that occur when the sow is engaged in one of the exclusively occurring behaviors.

$^c$ Behaviors that must be calculated from two consecutive depth images.
V₃ = portion of the feeder area (V₃ = 700 pixels which corresponds to 12% of the feeder area)

V₄ = average of d_all in lying + (average of d_all in kneeling – average of d_all in lying)/2 (V₄ = 31 cm).

V₅ = average of d_all in standing (V₅ = 64 cm)

V₆ = minimum value of x_head when feeding (V₆ = 9 pixels)

V₇ = average of d_shoulder when sitting (V₇ = 60 cm)

V₈ = the maximal x-coordinate value of the feeder (V₈ = 47 pixels)

V₉ = average of d_shoulder in standing (V₉ = 70 cm)

da. Determine drinking behavior that may happen concurrently with other behaviors such as standing, sitting or lying. Searching the sow pixels connected to or near the nipple drinker in horizontal distribution and their height greater than the height of the nipple drinker (V₇). If the result is greater than one third of the nipple drinker area (V₇), the sow is likely drinking. Due to the proximity between the feeder and the nipple drinker, in some cases when the sow was feeding her body might also seem to touch the nipple drinker. To distinguish this from true nipple drinker contact with other behaviors such as standing, sitting or lying.

b. Apply d_all, d_upper and d_lower as the lying-posture classification criteria. If d_all < V₆, the sow is classified as in lying posture. Once the sow is determined to be in her lying posture, another step combined with the drinkflag is used to further classify the sow’s lying posture into “udders facing heat lamp”, “udders facing heat lamp and drinking”, “backside facing heat lamp” or “backside facing heat lamp and drinking”. A separate paper will report this aspect of the sow’s behavior and the associated behaviors of the piglets. When examining the depth image of lying sow (Fig. 2) we can see that the udders side has a lower depth to the floor than the backside. In this study the heat lamp was located above the “upper part” of the image. Hence when d_upper is smaller than d_lower it means the sow taking the posture of lying with “udder facing heat lamp”. Conversely, when the d_upper is larger than d_lower it means that the sow taking the posture of lying with “backside facing heat lamp”.

c. If the sow is not in lying posture, d_all, d_head, d_hip, d_shoulder, d_loin and x_head combined with drinking recognition are used to classify the sow into “sitting”, “sitting and drinking”, “kneeling”, “standing and feeding”, “standing and exploring”, or “standing and drinking”. If d_all < V₅, x_head > V₆ and d_hip < d_shoulder then the sow is sitting; if d_all < V₅, d_shoulder < d_loin and d_shoulder < V₅ then the sow is kneeling; otherwise the sow is standing. When the sow is standing, the following rules are used to determine her standing type: if the sow’s head is above the feeder (x_head < V₆) and lowering her head to the feeder (d_head < V₅) it means she is feeding, otherwise she is merely standing or standing and drinking.

In part 3, shifting or movement is judged by comparing the behaviors between the current and the previous depth images. If the two behaviors are different, it means that shifting has occurred and the sow has changed her behavior. Movement is acquired by computing the change in the centroid location between the current and the previous depth images, namely.

\[
\text{Movement} = \sqrt{(X_{\text{centroid}1} - X_{\text{centroid}2})^2 + (Y_{\text{centroid}1} - Y_{\text{centroid}2})^2}
\]  

(3)

where centroid1 and centroid2 stand for the sow’s centroid in the respective image.

A total of 43,380 depth images and the same number of digital images were used to evaluate the performance of the recognition algorithm. The images were recorded from three farrowing crates over three days at 6 s intervals when the piglets were 5, 11, and 18 days of age.

The accuracy of behavioral classification is computed by the following equations.

\[
P_{\text{accuracy}} = 1 - P_{\text{FPR}} - P_{\text{FNR}}
\]  

(4)
The accuracies of the behavioral classifications by the image processing and analysis algorithm, relative to manual recognition, are presented in Tables 2–4. As shown by the data in Table 2, out of the 36,419 lying images, 36,382 were correctly identified or at a 99.9% accuracy, with 2 false positives (1 kneeling and 1 sitting postures) and 37 false negatives (31 as sitting, 5 as standing, and 1 as kneeling). Out of the 1818 total sitting events, the algorithm correctly recognized 1775 or at a 96.4% accuracy. Specifically, the algorithm incorrectly recognized 31 lying and 12 standing as sitting, resulting in a classification error \( P_{PFN} \) of 2.37%. In addition, 1, 19 and 2 of the 1797 sitting behaviors were incorrectly classified as lying, standing and kneeling, respectively, yielding a classification error \( P_{PFN} \) of 1.22%. Similarly, classification accuracy for standing and kneeling was 99.2%, and 78.1%, respectively. The overall classification accuracy of lying, sitting, standing and kneeling was 99.8%. The relatively lower classification accuracy for kneeling was caused by misclassification when the sow was sitting or standing with her neck or head lowered. The results also showed that over the three monitoring days the sows spent 84.0 (±0.9)% of time lying down, 4.1 (±0.8)% of time sitting, 11.8 (±0.6)% of time standing. The 84% lying time for the sows paralleled the literature report that pigs spend 75–80% of their time lying down (Velarde and Geers, 2007; Rolandsdotter et al., 2009; Whittaker et al., 1999).

The identified lying behaviors were further analyzed by comparing the average heights of upper and lower parts of the image to distinguish between the two lying orientations. For the 36,382 correctly recognized lying images, only three were incorrectly recognized between “backside facing heat lamp” and “udder facing heat lamp” orientations. The reason was that sometimes the piglets climbed on the sow's udder side which occasionally caused the height of the udder side greater than the backside, as shown in Fig. 4. The result suggests that the rule of comparing the average heights of the upper and lower parts of the sow to distinguish between back and udder sides worked well.

As shown by the data in Table 3, a total of 4038 feeding images were correctly classified and four were misclassified as others, but 102 other images were misclassified as feeding behavior, yielding a classification accuracy of 97.4%. For the drinking behavior, the algorithm correctly classified 1139 out of 1207 and incorrectly classified 16; it also misclassified 68 other behaviors as drinking, yielding a 92.7% classification accuracy. The lowest accuracy was associated with the shifting classification (63.9%). This outcome was partially attributable to the fact that when one image was misclassified it often resulted in two shifting errors. For example, if the second image of 3 consecutive standing images was recognized as sitting it would lead to two shifting classification errors: images 1–2 as “standing to sitting” and images 2–3 as “sitting to standing”. The primary cause is believed to be insufficient image sampling frequency, which missed some of the transitioning dynamics. This drawback, however, can be easily corrected in future studies.

Table 4 further summarizes the distribution of sow’s sitting, standing, feeding and drinking behaviors over the three monitoring days. On average the sows spent 43.6% of sitting time drinking, 78.8% of standing time feeding, and 15.4% of standing time feeding and drinking.
Fig. 4. Piglets on the sow’s udder side could lead to incorrectly recognized lying orientation.

Fig. 5. Movement of a sow’s centroid on 5th, 11th and 18th day of lactation.

Fig. 6. Diurnal hourly movements of a sow’s centroid on three lactating days.
exploring. It can also be noted that the sows tended to drink more while sitting (67.8%) than while standing (25.7%) or lying (6.4%).

Fig. 5 depicts the movement of centroid of a sow during three monitoring days. Fig. 6 depicts diurnal hourly movements of the sow. From Fig. 6 it can be seen that the sow tended to be more active during the period of 02:00 to 12:00 h than the rest of the day. The sow also showed increased activity levels as the piglets grew. This outcome presumably resulted from the sow needing to increase feed intake to meet the increasing milk demand by the growing piglets. In fact, the sow’s lying time changed slightly from 84.7% when the piglets were 5 days old to 83.0% when the piglets were 18 days old; but the sow’s daily feeding time increased from 136 min to 174 min during the same period.

4. Conclusions

An algorithm was developed and applied that automatically processes and analyzes depth images of sow’s lying, sitting, standing, kneeling, feeding, drinking, shifting and moving behaviors in farrowing crates. Classification of the sow behaviors with the algorithm demonstrated high degrees of accuracy. Data from limited number of animals confirm that the sow spends a much greater amount of time lying (84.0%) as compared to sitting (4.1%) and standing (11.8%). The sow’s moving activity increased with increasing piglet age. Future work should increase the frequency of depth image acquisition in order to better capture and quantify the sow’s behavioral transitioning and the associated implications in animal health and adequacy of facility design. Information of this nature is expected to provide insight for improved design and management of swine farrowing facility and operation, which will ultimately enhance animal welfare and improve the efficiency of resource utilization.

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