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Modelling and monitoring sows’ activity types in farrowing house using acceleration data

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Abstract

This article suggests a method for classifying sows’ activity types performed in farrowing house. Five types of activity are modeled using multivariate dynamic linear models: High active (HA), Medium active (MA), Lying laterally on one side (L1), Lying laterally on the other side (L2) and Lying sternally (LS). The classification method is based on a Multi Process Kalman Filter (MPKF) of class I. The performance of the method is validated using a Test data set. Results of activity classification appear satisfying: 75 to 100\% of series are correctly classified within their activity type. When collapsing activity types into active (HA and MA) vs. passive (L1, L2, LS) categories, results range from 96 to 100\%. In a second step, the suggested method is applied on series collected for 19 sows around the onset of farrowing, including 9 sows that received bedding materials (57 sow days in total) and 10 sows that received no bedding material (61 sow days in total). Results indicate that there is a marked i) increase of active behaviours (HA and MA, \( p < 0.001 \)) and ii) decrease of lying laterally (L1 and L2) behaviours starting 20 to 16 hours before the onset of farrowing; during the last 24 hours before parturition, the averaged time spent lying laterally in a row decreases and the number of changes of activity types for HA and MA increases. These behavioural changes occur for sows both with and without bedding material, but are more marked when bedding material is provided. Straightforward perspectives for applications of this classification method for monitoring activity types are e.g. automatic detection of farrowing and detection of health disorders.

Keywords: Acceleration, Body activity, Dynamic Linear Models, Multi Process Kalman Filter, Parturition.

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1. Introduction

Development of automation systems for pig production has, so far, mainly focused on reproduction management - with emphasis on oestrus detection (Bressers et al., 1991; Cornou, 2006, 2007; Cornou et al., 2008; Freson et al., 1998; Geers et al., 1995; Korthals, 1999; Blair et al., 1994) -, health disorders (Madsen et al., 2005; Ferrari et al., 2007; Silva et al., 2007) or on the measure of live weight for growing pigs (Frost et al., 2004; Brandl and Jørgensen, 1996; Lind et al., 2005; Schofield, 2007).

In farrowing house, attempts have been made to develop automatic methods for detecting the onset of parturition. These methods are based on monitoring nest building behaviour (or, more generally, an increase in activity) and changes of body temperature. For crate-confined sows, Bressers et al. (1994) used a radiotelemetric device implanted under the ear base. Erez and Hartsock (1990) studied changes in one sow’s body postures prior to parturition using an infrared photocell system mounted on farrowing crates. Oliviero et al. (2008) used two kinds of movement sensors to detect the onset of farrowing: a force sensor that measured the overall movement of the sows and photocell was placed at a height of 0.6 m that detected whether the sow was lying down or standing up. Accelerometers have previously been used to monitor the activity of individual sows: Cornou and Lundbye-Christensen (2008, 2010) suggested monitoring methods to classify activity types for sows housed in a large pen; 3-dimensional accelerometers have also been used for monitoring cows’ behaviour patterns (Martiskainen et al., 2009).

The objective of this study is to develop a method that automatically monitors the behaviour of periparturient sows housed in farrowing crates. The suggested method aims at classifying specific activity types using acceleration measurements; it is then used to assess behavioural deviations around the onset of farrowing, for sows with and without provision of bedding material. After presentation of the material and methods in Section 2, Section 3 describes the classification method. Results are presented in Section 4 and discussed in Section 5.

2. Material and Methods

2.1. Animals, housing and measurements

A total of 24 sows (Landrace × Yorkshire) were monitored in the farrowing house of a production herd, in Zealand, Denmark, from May the 27th until June the 13th, 2008. Sows were dry-fed three times daily (7.15 am, 12.00 pm and 15.30 pm) and kept in crates of dimensions 60 cm wide and 195 cm long, inside of a pen of dimension 155 cm wide and 225 cm long. During pregnancy, sows were kept loose-housed in groups of approximately 100 individuals.

Sows were monitored from their entrance into the farrowing house, and during 7 days (for 11 individuals, first batch) and 11 days (for 13 individuals, second batch).

Because the slurry tank of the farrowing house had limited capacity for absorbing straw, sows were divided in two groups. In each group, half the individuals (6 and 7, respectively), received approximately 0.5 kg straw as bedding material every second day (Group S). The rest received no bedding material (Group NS). Sows’ parity ranged...
from 1 to 8, with an average ± SD of 3.8 ± 1.8 (Group S: 4 ± 1.8; Group NS: 3.5 ± 1.9).

Sows’ activity was measured using a 3-dimensions digital accelerometer (LIS3L02DS from STMicroelectronics), at four samples per second, at a range 0-2g; accelerometers were calibrated such as 1 unit correspond to 0.1g. Each accelerometer (15.5 × 7.4 mm) was fixed on a board together with a blue tooth node, and put in a curve shaped air tight box of dimension 135 × 33 × 80 mm, together with 4 AA size batteries. The boxes containing the accelerometers were fixed on a neck collar and fitted on each experimental sow; the neck collars were fitted tight enough to limit its movements, in order for the box to stay below the neck. Data was transferred to a PC via two external Bluetooth dongles hanging down from the ceiling in the middle of the farrowing house. Sows’ activity was recorded four times per second, 24 hours a day. The sows were video recorded 24 hours a day using 12 cameras (TVCCD-140IR fra Monakor) hanging up above the pens, at about 3 meters high; one camera was used to monitor two sows. Artificial light was on during the night, in order to provide sufficient lightning for video recording: the light used was neon light normally used in the farrowing house, for daily work.

2.2. Data collected

Acceleration data from 19 sows were available, including 9 sows from group S and 10 sows from group NS. The unavailable time series were due to: three sows which sensors failed during the first experimental day; one sow that died during the experiment; series from a sow that farrowed after the end of the experiment has also been omitted.

Moreover, data was deleted from the time series in two cases: 1) in the periods when the sows lost their neck collar: a total of 91 hours, issue from 4 sows; 2) when data corruption was detected by the server.

Video recordings helped to determine which type of activity sows were performing in a given time interval and the exact onset of farrowing for each experimental sow.

3. Modelling and monitoring of the activity types

Five types of activity are initially chosen to describe the behaviour of sows in farrowing crates:

1. HA: High active behaviour, corresponding to feeding and rooting activities.
2. MA: Medium active behaviour, corresponding to standing, sitting or lying sternally, where the sow is active (i.e. not sleeping or resting).
3. L1: Lying on one side and passive, where the sow is sleeping or resting.
4. L2: Lying on the other side and passive, where the sow is sleeping or resting.
5. LS: Lying sternally and passive, where the sow is sleeping or resting.

Each of these activities is modeled using a multivariate dynamic linear model (DLM), applied on series previously averaged per second. Estimation of the activity specific variance parameters is performed using a Learning data set including 8 series per activity type (from 8 individuals from the first batch) of 10 minutes (i.e.
4800 observations, for each activity type), all extracted from a same day (May, 29th). The classification method is thereafter assessed on a Test dataset, which consists of 24 series (2 × 10 minutes from 12 individuals from the second batch) of 10 minutes (i.e. 28800 observations, for each activity type), all extracted from a same day (June, 5th). Series of each data set are selected by observing video recordings and associating the corresponding series extracts, as in Cornou and Lundbye-Christensen (2008); ?.

3.1. Modelling: Specifications of the multivariate DLMs

The multivariate DLM involves a three-dimensional observational vector \( (x_t, y_t, z_t) \) corresponding to the accelerations of the three-axes, and a three-dimensional latent process \( \theta_t \). The observation equation (1) describes the sampling distribution of the observation vector \( Y_t \) as:

\[
Y_t = \begin{bmatrix} x_t \\ y_t \\ z_t \end{bmatrix} = F_t^T \theta_t + \nu_t, \quad \nu_t \sim N(0, VI),
\]

assuming the observational noise to be normal, independent over coordinates, and with variance \( V \) and identity matrix \( I \).

The evolution over time of \( \theta_t \) is modeled as a random walk

\[
\theta_t = \theta_{t-1} + \omega_t, \quad \omega_t \sim N(0, W).
\]

The observation variance \( V_I \), is a diagonal \( 3 \times 3 \) matrix with a same parameter value for axes \( x, y \) and \( z \). The evolution variance \( W \) is a \( 3 \times 3 \) matrix with a completely free structure, allowing for correlation between the axes; this corresponds to the multivariate model M3 suggested in ? without sinoid component, reducing the dimension of the variance from \( 9 \times 9 \) to \( 3 \times 3 \) in this study.

The DLM estimates the underlying state vector \( \theta_t \) by its conditional mean vector \( m_t \) and its variance-covariance matrix \( C_t \) (the model variance) given all previous observations \( D_t = \{Y_1, \ldots, Y_t\} \) of the acceleration measurements. The conditional distributions are

\[
(\theta_t | D_t) \sim N(m_t, C_t), \quad (Y_t | D_{t-1}) \sim N(f_t, Q_t).
\]

The updating equations of the DLM used for stepwise calculation of \( m_t, C_t, f_t \) and \( Q_t \) can be found in (West and Harrison, 1997).

A separate DLM is fitted for the five activity types. Each activity is characterized by its activity-specific parameters: the observation variance \( V \) and the parameters of the system variance \( W \) of the respective activities, are estimated using the EM algorithm (Dempster et al., 1977; Dethlefsen, 2001; Jørgensen et al., 1996). The EM algorithm is an iterative algorithm used to estimate unknown parameters by maximum likelihood estimation. It uses the conditional mean vector \( m_t \) and model variance \( C_t \) (3), and their respective smoothed components \( \tilde{m}_t \) and \( \tilde{C}_t \) (West and Harrison, 1997).

Results of the estimated parameters converge after 800 iterations and are presented in Table 1. The estimated parameters indicate that the more active is a type of behaviour, the larger are the associated variances. For both HA and MA, most of the variance appears to be located in the diagonal components of the system variance \( W \),
where values are up to 80 times larger (for HA) than the corresponding observation variance \( V \).

Table 1: Results of parameter estimation for the five activity types for the Learning data set (4800 seconds observation). In columns: High active (HA), Medium active (MA), Lying side 1 (L1), Lying side 2 (L2), Lying sternally (LS). In rows: diagonal parameter for the observation variance \( V \), and diagonal parameters of the evolution variance \( W \) for the axes \( x (W_x) \), \( y (W_y) \) and \( z (W_z) \). Correlations between axes are not presented but available on request.

<table>
<thead>
<tr>
<th></th>
<th>HA</th>
<th>MA</th>
<th>L1</th>
<th>L2</th>
<th>LS</th>
</tr>
</thead>
<tbody>
<tr>
<td>( V )</td>
<td>2.5e^{-2}</td>
<td>6.4e^{-2}</td>
<td>1.3e^{-2}</td>
<td>1.1e^{-2}</td>
<td>6.6e^{-3}</td>
</tr>
<tr>
<td>( W_x )</td>
<td>1.1</td>
<td>2.5e^{-1}</td>
<td>5.2e^{-4}</td>
<td>1.2e^{-4}</td>
<td>1.7e^{-3}</td>
</tr>
<tr>
<td>( W_y )</td>
<td>2.2</td>
<td>3.6e^{-1}</td>
<td>2.6e^{-3}</td>
<td>3.6e^{-3}</td>
<td>8.4e^{-5}</td>
</tr>
<tr>
<td>( W_z )</td>
<td>9.6e^{-1}</td>
<td>6.7e^{-2}</td>
<td>4.3e^{-3}</td>
<td>2.6e^{-3}</td>
<td>2.8e^{-4}</td>
</tr>
</tbody>
</table>

As a control for consistency, an additional set of parameters is estimated using the first 10 minutes of each series of the Test data set (total of 7200 seconds observation). Results for the estimated parameters appear relatively similar, except for the activity type HA: the observation variance \( V \) estimated from the Test data set appears larger than the one from the Learning data set (0.5 vs. 0.025); this seems however compensated by smaller values of the evolution variance (0.36, 0.51 and 0.34 vs. 1.1, 2.2 and 0.96 for \( W_x \), \( W_y \) and \( W_z \), respectively for Test and Learning data sets). The fact that the Test data set includes a larger number of sows (12 vs. 8) and the use of few series of different lengths (i.e. 6 and 4 minutes initially set together, instead of 10 minutes in a row) may have influenced the distribution of the variance within the parameters \( V \) and \( W \) during parameter estimation.

3.2. Monitoring: Classification method for activity types

Automatic classification of the activity types is performed by a Multi-Process Kalman Filter (MPKF) of class I, as in Cornou and Lundbye-Christensen (2008); ?. Each DLM is characterized by the variance parameters \( M_t : \alpha(i) = [V(i), W(i)] \) where \( \alpha(i) \) holds for all \( t \); there is uncertainty about the ‘true’ value of the defining parameter vector \( \alpha(i) \), where \( \alpha(i) \) is the set of parameters for the 5 possible DLMs, i.e. the five activity types indexed by \( i \in \{ \text{HA, MA, L1, L2, LS} \} \). Each DLM, \( M_t(\alpha(i)) \), is analyzed using the updating equations. At each time \( t \), the posterior probabilities \( (p_t(i)) \) are calculated for each \( i \), as

\[
p_t(i) \propto \phi_t(i) \times p_{t-1}(i),
\]

where \( \phi_t(i) \) is the predictive distribution of the observation given both the past \( D_{t-1} \), and that model \( i \) is appropriate.

Each DLM is analyzed using the variance parameters estimated from the Learning data set. Initial values of the probabilities are set to 0.2, corresponding to a uniform distribution for the five activity types. Detailed descriptions of the classification method can be found in Cornou and Lundbye-Christensen (2008); ?.
3.3. Validation of the classification method

Validation of the classification method is performed using series divided into 2 min intervals. The Test data set is analyzed using the parameters of the Learning data set. Additionally, the parameters previously estimated using the Test data set, are used to analyze the Learning data set.

Output results are computed as follows: i) for each observation (i.e. each second), the activity type result (observation result) is determined as being the one with the highest posterior probability. ii) for each 2 min interval, the activity type which has the largest number of observation results is determined as series result. Because of learning characteristic of the updating equations, series results are computed only for the last 60 seconds of the 2 min interval. iii) finally, correction for lying position is performed according to the mean value of the axes x or z for the given interval: $\bar{x} > 7.5$ for L1, $\bar{x} < 7.5$ for L2, and $\bar{z} < 7.5$ for LS. The threshold of 7.5 was chosen by observing series corresponding to the respective activities (L1, L2 and LS).

3.4. Statistical analyses

After classification of the series into activity types and to assess potential differences in the activity patterns at the approach of farrowing, the entire experimental period is divided into 24 hours intervals around farrowing. These intervals are computed for each sow, around the onset of farrowing ($h_0$). In each interval, three key figures are analyzed for each day:

- The proportion of time spent performing a certain activity type.
- The number of changes from a given activity: a change of activity is computed each time a sow’s activity type, as classified by the MPKF, changes from one to another e.g. when a previous 2 min series is classified as L1, and the next as MA. Changes of activities may be used as an indicator of, for instance, restlessness.
- The number of 2 min series classified as a same activity, without interruption.

The proportion of time spent performing a certain activity type was analyzed in R using the `lmer` function of the `lme4` library according to the following generalized linear mixed model:

$$
\log\left(\frac{p_{ijk}}{1-p_{ijk}}\right) = \mu + \alpha_i + \beta_j + S_k, \quad (5)
$$

where $p_{ijk}$ is the proportion of time spent performing a certain activity type on day $i \in \{-4, \ldots , 4\}$ for sow $k \in \{1, \ldots , 19\}$ in group $j \in \{S, NS\}$, $\mu$ is the mean, $\alpha_i$ is the fixed effect of day $i$, $\beta_j$ is the fixed effect of group $j$, and $S_k \sim N(0, \sigma_s^2)$ is the random effect of sow $k$.

Both the number of changes from a given activity and the number of 2 min series classified as a same activity (without interruption) were analyzed in R using the `lmer` function of the `lme4` library using a Poisson regression model:

$$
\log(EY_{ijk}) = \mu + \alpha_i + \beta_j + S_k, \quad (6)
$$
where the response variable $Y_{ijk}$ is i) the number of change from a given activity or ii) number of 2 min series classified as a same activity (without interruption) on day $i \in \{-4, \ldots, 4\}$, for sow $k \in \{1, \ldots, 19\}$ in group $j \in \{S, NS\}$, $\mu$ is the mean, $\alpha_i$ is the fixed effect of day $i$, $\beta_j$ is the fixed effect of group $j$, and $S_k \sim N(0, \sigma^2_S)$ is the random effect of sow $k$.

4. Results

The classification method is applied on series of acceleration measurements collected for the 19 sows, previously averaged per second and divided into 2 minutes intervals. Output results are computed as in Section 3.3.

Results for both Test and Learning data sets are presented in Table 2. The percentage of series correctly classified by the MPKF is seen in diagonal. For both data sets, the activity types L1, L2 and LS are best recognized; for the Test data set (left panel) 2 to 5% of these activities are misclassified as MA. Small movements performed by a sow when sleeping, which may result in brief increase of acceleration (and recognition as MA by the MPKF), is a likely explanation for these misclassified series.

For HA activity type, 9.4 and 7.5% of the series, respectively for Learning and Test data sets, are misclassified as MA. This can be explained by the fact that while performing HA activity type, sows tend to reduce the intensity of their activity for few seconds for instance, which is that case become classified as MA. The same type explanation holds for MA activity types, where short periods of more intense activity can be observed, and classified as HA (20.8 and 12.5%, respectively for Learning and Test data sets). It should furthermore be noticed that even though differences in HA parameters values were observed between the Test and Learning data sets, results of the classification method, using both parameters sets, appear consistent. It can be noticed that no HA series is misclassified as passive activity (L1, L2, LS), as well as none of the passive series is misclassified as HA.

Table 2: Results of the MPKF for the five activity types, applied for both Test data set (using parameters from the Learning data set) and Learning data sets (using parameters from the Test data set). In columns: High active (HA), Medium active (MA), Lying side 1 (L1), Lying side 2 (L2), Lying sternally (LS). In rows: percentage of series results, for the five activity types, as classified by the MPKF.

<table>
<thead>
<tr>
<th></th>
<th>MPKF on Test set</th>
<th></th>
<th>MPKF on Learning set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HA</td>
<td>MA</td>
<td>L1</td>
</tr>
<tr>
<td>HA</td>
<td>96.0</td>
<td>94.0</td>
<td>0</td>
</tr>
<tr>
<td>MA</td>
<td>20.8</td>
<td>75.0</td>
<td>0</td>
</tr>
<tr>
<td>L1</td>
<td>0</td>
<td>2.1</td>
<td>97.9</td>
</tr>
<tr>
<td>L2</td>
<td>0</td>
<td>3.1</td>
<td>96.9</td>
</tr>
<tr>
<td>LS</td>
<td>0</td>
<td>5.2</td>
<td>0</td>
</tr>
</tbody>
</table>

When grouping the activity types into active (HA and MA) vs. passive (L1, L2 and LS) categories, the percentage of series correctly classified is 98% and 96% for the active categories, respectively for Test and Learning data sets; the passive categories are correctly classified as passive for 97% and 100% of the series, for Test and Learning sets, respectively.
Additionally, i) results from series where the number of missing observations is above 50% are classified as missing value; ii) Neck collars that have loosen during the experiment may result in a change of the accelerometer box position: re-classification of the passive activities as L1, L2 or LS using the suggested thresholds is in some cases not possible (due to different axes values) and the lying position is then classified as unclear (LU); iii) finally, since misclassification due to sow moving in sleep, or less active in active period, a single outlier filtering is performed: an isolated single interval classified as active behaviour (HA or MA), which is located inside a series of passive behaviour (L1, L2, LS or LU), is re-classified as the previous passive behaviour type, and reciprocally. This re-classification, or filtering of the qualitative series is performed for 7% of the 2 min intervals.

Figure 1 illustrates the output results from the MPKF applied for a series of acceleration measurements of 24 hours, corresponding to two days prior the farrowing day, for sow 1 of group S. The time series of acceleration measurements (a) are averaged per 10 seconds, for better graphical display.

The output results (b) shows three main periods of high activity (HA), corresponding to the feeding time (07:15, 12:00 and 15:30). These periods of high activity are usually surrounded by periods of medium activity, corresponding to a sitting, standing or lying sternally position. Medium activity (MA) or lying sternally and passive (LS) are mostly observed in day time. From 18:00 to 05:00, output results show that the sow
is mainly lying laterally (L1 or L2).

Figure 2 shows the series and corresponding output results for the same sow as Figure 1, at the day of farrowing. The vertical dotted line indicates the onset of farrowing.

The bottom plot (b) shows that periods of high activity (HA) are stretched outside the feeding time and are almost continuous from 07:00 until about two hours before the onset of farrowing. Periods of high activity are in that case associated not only with feeding, but also with nest building behaviour (also when no bedding material is provided), as observed on video. Besides, it can be seen that the averaged length of activity types (i.e. time used performing a same activity without interruption) appears shorter.

To assess potential differences in the activity patterns at the approach of farrowing, periods of 24 hours are computed for each sow, around the onset of farrowing (h0). Analyzed are performed according to Section 3.4.

Figure 3 illustrates, for each 24 hours interval, the percentage of time spent performing the different activities, for sows receiving bedding material (a) and sows receiving no bedding material (b); d0 represents the last 24 hour period before the onset of farrowing (i.e. h-24 to h0). The variation in the number of sows behind the averaged bar plots is a result of i) the difference in length of the experimental periods: 7 days for the first batch and 11 days for the second batch; and ii) the difference in the onset of
farrowing for the experimental sows. Only complete intervals of 24 hours are included.

For both groups, it can be seen that the percentage of time spent performing active behaviour increases significantly during the last 24 hours before farrowing. The sum of HA and MA activities reaches 62.8% (±13.4) (group S) and 56.4% (±16.4) (group NS), as compared to a daily average of 30.0% (±5.0) (group S) and 25.6% (±6.2) (group NS) for the other days. The higher standard deviation observed for active behaviours for group NS indicates larger variation in active behaviours among sows where no bedding material is provided.

The time spent lying laterally (L1 and L2) decreases on d0. The percentage of misclassified Lying and passive (LU) activity is rather small: 4.8% in average, for the 19 sows for the entire experimental period. The total number of 2 min series classified as LU ranges from 13 to 715 for the 19 sows (average of 239 ± 171). Series from four sows (for which the LU 2 min periods totals at 396, 449, 464 and 715) represent 44.6% of these series. This may be explained by the fact that these specific sows had more loosen neck collars than the others.

Applying Model (5) with activity type HA as response confirms the impression from Figure 3 of a highly significant effect of day with d0 at a much higher level than all other days (p < 0.001). Odds ratios defined with day -4 as reference (OR=1) are shown in Table 3. As it is also seen in the table, sows in group S show a higher proportion of time spent performing activity type HA (odds ratio 1.37, p = 0.02) than those in group NS. Days -6, -5 and +5 are omitted so that only days where both groups have data are included in the analysis.

For the activity type MA a similar pattern is seen in Table 3. Again, d0 is at a much higher level than all other days. Furthermore, there seems to be higher levels for MA in the days before farrowing than the days after farrowing. Even though sows in group S also in this case show a higher proportion of time spent performing the activity (odds ratio 1.22), the effect is in this case not significant (p = 0.11). Applying model (5) using the total activity (sum of HA and MA) as response variable shows an OR of 3.93 at d0 (p < 0.001), and a significant effect of Straw (p = 0.047).

The left side of Figure 4 shows the number of changes of activity types sows per-

<table>
<thead>
<tr>
<th>Day</th>
<th>OR HA</th>
<th>p</th>
<th>OR MA</th>
<th>p</th>
<th>Group</th>
<th>OR HA</th>
<th>p</th>
<th>OR MA</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>-4</td>
<td>1.00</td>
<td>-</td>
<td>1.00</td>
<td>-</td>
<td>NS</td>
<td>1.00</td>
<td>-</td>
<td>1.00</td>
<td>-</td>
</tr>
<tr>
<td>-3</td>
<td>0.97</td>
<td>ns</td>
<td>1.12</td>
<td>≪ .001</td>
<td>S</td>
<td>1.37</td>
<td>.02</td>
<td>1.22</td>
<td>0.11</td>
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<td></td>
</tr>
<tr>
<td>-1</td>
<td>1.21</td>
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<td>1.12</td>
<td>≪ .001</td>
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</tr>
<tr>
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<tr>
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Figure 3: Average time spent performing each activity type (in percentage), for the group S (a) and group NS (b). From left to right: 24 hours intervals around farrowing (d0 is the last 24h before the onset of farrowing); Within the bar plots: distribution of the 6 activity types; Top of the bar plots: number of sows included in the average.
form, for each 24 hours period, for sows from group S (a1), and group NS (b1). For both groups, the number of changes of activity type is strongly increasing from d-1 to d0, both for HA (×2.7 and ×2.6, for group S and NS, respectively) and MA (×2.0 and ×2.0, for group S and NS, respectively). The averaged number of changes for lying laterally (mean value for L1 and L2) stays relatively constant over the entire period, for both groups.

![Daily averaged number of activity changes](image1)

![Daily averaged length of activity, per 2 min](image2)

Figure 4: Daily averaged number of changes of activity type for sows in group S (a1) and NS (b1), and daily averaged length (in number of 2 min intervals per 24h) used performing the activities for group S (a2), and NS (b2): HA (plain line), MA (dashed line) and mean for lying laterally (L1 and L2) positions (points). Horizontal axis: 24 hours intervals around farrowing (d0 is the last 24h before the onset of farrowing).

The right side of Figure 4 shows the length, or number of 2 min series per 24 hours classified as a same activity (without interruption), for the group S (a2) and NS (b2). It is seen that the averaged length for the lying laterally positions is strongly reduced at d0 (×0.44 and ×0.52, respectively for group S and NS) while the length of the periods
for HA and MA activities stay rather stable. It should be noticed that results from d-6, d+3 and d+4 for group S, as well as d+4 and d+5 for group NS are issue from a single individual (as indicated in Figure 3, on top of the bar plots).

Applying Model 6 to the total number of changes for all six activities (sum of HA, MA, L1, L2, LS and LU), a significant effect is observed at d-1 and d0 ($p < 0.001$). The estimated mean ($\mu$) for activity changes is twice as large at d0, as compared to all other days. The effect of Straw is not significant.

Applied on the daily averaged number of 2 min series classified as Lying Laterally without interruption (sum of LL1 and LL2), the effect of day is highly significant. The estimate is twice reduced at d0 (0.46), as compared to 0.78 at d1, and values ranging from 0.94 to 1.1 for the other days. The effect of Straw is here again, not significant.

Figure 5 illustrates the percentage of time spent per hour, performing HA, MA and lying laterally (sum of L1 and L2) activities. Results are shown from 48 hours before the onset of farrowing (h0) until 24 hours after.

For both groups, a decrease of lying laterally (L1+L2) activities, and increase of active behaviours, is observed from between h-20 to h-16. This decrease of time spent lying laterally is more pronounced for group S, from h-13 to h-4. A peak of MA is observed for group S: 62% of time spent per hour h-13 and h-12. As for MA, the increase of HA is more marked for group S: from h-16 to h0, the percentage of HA represents 30% for group S vs. 22% for group NS. A peak of HA behaviour is observed for both groups 4 hours before farrowing.

The percentage of time spent lying laterally reaches its highest level from about 4 hours after farrowing, and appears stable the following 24 hours.
Figure 5: Percentage time spent performing each activity type per hour, for the group S (a) and group NS (b), from 48 hours before the onset of farrowing (h0) to 24 hours after: HA (bar plots), MA (plain line) and sum of Lying laterally L1 and L2 (points).
5. Discussion and Conclusion

The method suggested in this article aims at classifying sows’ activity types performed in the farrowing house. After validation of the method using data sets including some given known series, data collected for 19 sows around the onset of farrowing are analyzed.

The classification method is based on a Multi Process Kalman Filter (MPKF) of class I, where each activity type is modeled using a multivariate DLM. Results of activity classification appear satisfying: 75 to 100% of series are correctly classified within their activity type (HA, MA, L1, L2, LS). When collapsing activity types into active (HA and MA) vs. passive (L1, L2, LS) categories, results range from 96 to 100%.

It deserves notice that what is here determined as misclassified series may be due to the fact that series of measurements, even though of short duration (2 minutes), are rarely entirely homogeneous: short increases of acceleration, for instance due to small movements performed by the sow when sleeping, or few observations of less intense activity in series of high active behaviours are very likely to occur.

Three passive activity types are initially chosen: Lying laterally on one side (L1), the other side (L2), and sternally (LS). Parameters specific to these three types are estimated, and thereafter used in the classification method; values of estimated parameters are rather similar to each others, and it can be argued that a single set of parameters, corresponding to passive type could be used. This can be supported by the fact that, even though passive category is very well recognized, the MPKF alone, using activity specific parameters, performs poorly in distinguishing between the three respective passive activities (L1, L2 and LS). Before correction for lying position of the passive activities L1, L2 and LS, using the mean acceleration value of the axes x and z, recognition of the three passive activity types on the Test data set is 9, 17 and 78%, as compared to 98, 97 and 95% after axes correction. Axes’ values alone can however not be used to directly classify passive activity types: looking at averaged axes values, in particular z, could easily lead to misclassification; moreover, passive activity would be misclassified as active in the case of loosen neck collars, which can result in biased axes values.

Output results are computed for series of acceleration measurements previously divided into 2 min intervals. Initial posterior probabilities are set to 0.2, corresponding to a uniform distribution; an alternative would be to use the very last observation result of the previous series as initial prior for the next 2 min series. The choice of 2 min intervals is motivated by the fact that i) the updating equations may take time to recognize an activity (set here to 60 seconds), and ii) some activity types, especially feeding activity, are of short duration (approximately 10 minutes for feeding). If longer series intervals are used for classifying activity types, a moving window indicating when an activity change occurs could be used.

Perspectives for application of the classification method suggested in this article are straightforward. Detecting the onset of farrowing by monitoring behavioural deviations is one obvious automatic method that can be built upon activity classification. As results indicate, there is a marked i) increase of active behaviours and ii) decrease of lying laterally behaviours starting 20 to 16 hours before the onset of farrowing; the time spent performing a same activity in a row, or number of changes of activity time
can also be used as relevant variables to monitor the onset of farrowing. Even though these behavioural changes occur for sows both with and without bedding material, differences in intensity for the two groups are observed; this should be taken into account when developing a method monitoring the onset of farrowing.

Results indicate that sows which are provided with bedding material have an increase of high active behaviours more marked than the ones where no bedding material is provided. This is in accordance with the fact that, more generally, increasing space and provision of bedding material promotes nest building behaviour: in loose-kept farrowing sows (housed in 'get-away-pens') Thodberg et al. (1998) reported that access to straw increases the duration from the onset of nest building and rooting until farrowing, and increases the quantity of these activities. Nest building behaviour was also found more elaborated and started sooner for sows housed in 'get-away-pens', as compared to sows housed in crates (Thodberg et al., 2002). Damm et al. (2003) report that in the Swiss farrowing pen, the Schmid pen, sows performed more nest building behaviour (P=0.004).

The suggested method is applied on series of acceleration measurements collected for sows individually housed in crates. Previous attempts for monitoring behavioural deviations at the onset of farrowing used infrared photocell and force sensors mounted in the farrowing crates (Erez and Hartsock, 1990; Oliviero et al., 2008). As compared to these other technologies, the use of accelerometers fitted on each sow makes it possible to apply the method in any type housing systems, as well as for other types of farm animals; an example of application for a group of dairy cows is found in Nadimi and Soegaard (2009), where the authors also used dynamic linear models.

Besides, in the farrowing house, the fact that more space and bedding material improve the quantity and intensity of nesting behaviour, it can be assumed that alternative, more welfare friendly housing systems would favor a better detection of parturition for a system based on monitoring high active behaviours.

Other perspectives for application of the method suggested in this article are monitoring i) sows' health disorders occurring around farrowing; and ii) behaviour of sows at risks for piglet crushing, by monitoring particular activities, especially lying behaviour (Damm et al., 2005; Andersen et al., 2005).

In conclusion, the method suggested in this article allows to correctly classify 75 to 100% of activity types and 96 to 100% of activity categories. Results based on series from 19 sows indicate marked behavioural deviations the day before farrowing. Development of an automated method for detecting the onset of parturition, based on this classification method, appears straightforward.

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References


