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Automatic detection of oestrus and health disorders using data from electronic sow feeders

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Abstract

This article suggests a method for detecting oestrus, lameness and other health disorders for group housed sows fed by electronic sow feeders (ESF). The detection method is based on the measure of the individual eating rank, modeled using a univariate Dynamic Linear Model. Differences between the predicted values of the model and the observations are monitored using a control chart: a V-mask is applied on the cumulative sum of the standardized forecast errors of the model. According to the respective V-mask parameters, alarms are given for each of the three states (oestrus, lameness, others) when the deviations between model predicted values and observations exceed some defined parameters. External information is incorporated into the model to limit the number of false alarms when a subgroup of sows enters and exits a group or both. The detection method was implemented on data collected within three production herds over 12 months. Visual recordings were performed to identify sows in oestrus or with health disorders. The detection method showed a high specificity. For oestrus detection, there was a sensitivity of 59\%, 70\% and 75\% for the three herds as compared to 9\% (herd 1) and 20\% (herd 2) using lists of sows as alarms. Monitoring lameness results in a sensitivity of 56\%, 70\% and 41\%, vs. 39\%, 32\% and 22\% using the lists; monitoring other health disorders resulted in a sensitivity of 0\%, 75\% and 39\% for the three respective herds, vs. 34\% and 16\% for herds 2 and 3 using the lists. To limit the number of false alarms, it is suggested to expand the model by including daily feed intake or body activity as other response variables.

Key words: Group housed sows, ESF, Dynamic Linear Models, V-mask, oestrus, lameness, health status

1. Introduction

Group housing for sows results in difficulties monitoring an individual among a group; concomitantly, the increasing herd size implies a reduction of the time spent per animal. New automatic tools need may help farmers focus on specific individuals that need particular attention at a given time, for instance at the onset of oestrus or when health problems occur.
Eating behaviour is influenced by the onset of oestrus and diseases. For gilts, Friend (1973) reported a reduced feed intake from 23.56 ± 0.39 kg in weeks between successive oestrus to 19.90 ± 0.38 kg in weeks when oestrus occurred. It is suggested that the effect of oestrus on appetite is caused by oestrogens (Forbes, 1995). Furthermore, sows presenting health disorders will also modify their eating behaviour: a reduced feed intake is considered to be one of the first signs that an animal is ill (Forbes, 1995; Whittemore, 1998).

For group housed sows fed by electronic sow feeders (ESF), it is possible to collect sufficient information to characterize the eating behaviour of individual animals. At the present time, however, the information available to the farmer is restricted to a list of sows that have not eaten. A first attempt to model eating behaviour using a Multi Process Kalman Filter failed; explanatory factors were large variability observed among individuals, a limited number of sows (twenty unsuccessfully mated sows were monitored) and an inadequate model (Søllested, 2001). It is expected that selecting and processing the relevant information from ESF over a sufficient period of time and for a larger number of sows should allow development of a method for monitoring oestrus and health disorders.

Since group-housed sows fed by ESF do not have the possibility to eat simultaneously, it is expected that the order in which each sow accesses the ESF is defined by their rank in the group hierarchy. Hunter et al. (1988) and Connell et al. (2003) observe a positive correlation between the social rank in the group hierarchy and the individual eating rank; the individual eating rank is shown to be relatively stable over time (Bressers et al., 1993b; Edwards et al., 1988). Another factor influencing eating behaviour is the start of the daily feeding cycle (Jensen et al., 2000; Edwards et al., 1988). Group size also influences eating behaviour: more fights are observed within larger groups due to a greater number of ranks to attribute (Arey and Edwards, 1998). Finally, it is expected that the frequency of group mixing affects eating behaviour by influencing hierarchical rank attribution (Edwards, 2000; Spoolder et al., 1997; Arey, 1999; Bressers et al., 1993a).

The present study was designed to evaluate the potential of ESF measurements in detecting oestrus, lameness and other health disorders for group housed sows.

2. Experimental Procedures

2.1. Data collection
Data was collected over a period of 12 months (January 2005 to January 2006) in three production herds in Denmark.
2.1.1. Structures of the groups within each herd

In the three herds, the sows were introduced in the group from 1 to 5 days after mating (day 0) and transferred to the farrowing house from day 105 to day 115. Herds 1 and 2 had dynamic groups (3 and 10 pens, respectively) while herd 3 had static groups (9 pens). Other characteristics of herd management for the three herds are shown in Table 1.

The number of sows introduced per group was generally a function of the herd size. In herd 3, with static groups, the number of sows introduced and taken out should in principle be equal to the group size; in practice, however, this number is reduced due to frequent movements of individual sows that return to oestrus or are ill. In herds 1 and 2, with dynamic groups, sows may be taken in or out at any time.

2.1.2. Information collected by ESF

A central computer recorded visits at the ESF for the individual sows. All herds were equipped with ESF from SKIOLD Echberg A/S (Ikast, Denmark) starting daily feeding cycle at 17:00, 22:00 and 21:30 for herds 1, 2 and 3, respectively. In all herds, the duration of a feeding cycle was 24 hours; for herd 1 and 2, the ESF was closed 5 and 4 hours, respectively, before the start of a new feeding cycle. Table 2 presents the characteristics of the use of the ESF for the three herds. The average use of the ESF was stable from one herd to the other, but a large intra-herd variation was observed.

For all herds, the feed energy value was 0.95-1.05 FUp.kg\(^{-1}\) of dry feed (Feed Units, pigs: 1 FUp = 7.380 MJ net energy), and water was available in a bowl adjacent the feed bowl. Transfer from a part of a daily ration not eaten did not exceed 1 kg from one day to another.

2.1.3. Individual control of oestrus and health status

For the purpose of implementing a detection method for oestrus, lameness and other health disorders, these three conditions were observed daily for each individual sow by the herd employees: Back Pressure Test (Willemse and Boender, 1966) was performed to detect oestrus and visual observations were carried out for identifying lameness and other health disorders. Identification of a sow presenting one of these conditions was recorded when the individual was at the ESF or by applying an electronic reading to the individual ear tag. Every second week, a technician visited each of the three herds in order to ensure the registration quality of the observations. Each ESF was checked every two months. Registration was also performed each time a subgroup of sows entered the group, left the group or when subgroups entered and left a group the same day.

2.2. Modeling of the individual eating behaviour
The modeling of the eating behaviour and the detection method were implemented in the software R (R Development Core Team, 2005).

2.2.1. Definition of the response variable
The individual eating rank was selected as the response variable: it includes the order in which sows enter the ESF, the group size, and the start of the daily feeding cycle.

From the starting time of the daily feeding cycle at day \( t \), the order, \( o_{it} \), of sow \( i \) visiting the ESF, and eating more than 300 g, was calculated. Afterwards, the relative eating rank \( o^*_{it} (0 < o^*_{it} < 1) \) was calculated as:

\[
o^*_{it} = \frac{o_{it}}{N_t + 1}
\]

where \( N_t \) is the total number of sows in the group on day \( t \). To obtain an approximately normal distribution, the individual eating rank was logistically transformed as:

\[
O_{it} = \log\left(\frac{o^*_{it}}{1 - o^*_{it}}\right) = \log\left(\frac{o_{it}}{1 + N_t - o_{it}}\right)
\] (2)

When a sow had not eaten at the end of a daily feeding cycle, the individual eating rank \( o_{it} \) was set to \( N_t \), so that \( O_{it} = \log(N_t) \). From (2) it is apparent that a sow eating first receives the smallest \( O_{it} \) value, while a sow eating last (or not at all) receives the largest \( O_{it} \) value. Time series of daily eating ranks were generated for each experimental sow, for their entire gestating period. Since only one sow is modeled at a time, the index \( i \) for sow is omitted in the rest of the paper.

Figure 1 shows the development of the eating rank through a gestation period, both before (a1 and b1) and after (a2 and b2) logarithmic transformation; it is seen that the logarithmic transformation increases the stability of the variable over time. Figure 1 (a2) shows a pattern characteristic of the dynamic groups, as in herd 1 and 2: sows presenting a low eating rank had the opportunity to increase their rank when sows with higher rank exit the group. On the other hand, Figure 1 (b2) illustrates that a sow in a static group, as in herd 3, maintained a relatively constant eating rank over a longer period of time.

2.2.2. Model design
The individual eating rank was modeled using a Dynamic Linear Model (DLM) as described by West and Harrison (1997). The general DLM is represented as a set of two equations. The observation equation (3) defines the sampling distribution for the observation \( O_t \) conditional on a state vector \( \theta_t \). The system equation (4) defines the time
evolution of the state vector $\theta_t$. The matrices and state vector are defined in (5): $F_t$ is called the design matrix and $G_t$ is called the system matrix; $\theta_t$ consists of a set of parameters describing the model level ($\mu_t$) and growth ($\beta_t$) at time $t$. The error sequences $\nu_t$ and $\omega_t$ are assumed internally and mutually independent.

$$O_t = F_t^T \theta_t + \nu_t, \quad \nu_t \sim N(O,V)$$  
$$\theta_t = G_t \theta_{t-1} + \omega_t, \quad \omega_t \sim N(0,W)$$  
$$F_t = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \quad G_t = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}, \quad \theta_t = \begin{pmatrix} \mu_t \\ \beta_t \end{pmatrix}$$ (5)

The DLM combined with a Kalman Filter (KF) (Kalman, 1960) estimates the underlying state vector $\theta_t$ by its mean vector $m_t$ and its variance-covariance matrix $C_t$ (the model variance) given all previous observations $O_1, \ldots, O_t$ of the transformed eating rank. Thus, the conditional distribution of $\theta_t$ is

$$(\theta_t | O_1, \ldots, O_t) \sim N(m_t, C_t)$$ (6)

The updating equations of the KF used for stepwise calculation of $m_t$ and $C_t$ are found in West and Harrison (1997). Applications of the KF have been described previously e.g. in Thysen (1993), de Mol et al. (1999) or Madsen et al. (2005).

The observational variance ($V$) depends on the accuracy of the measurements by the ESF; this accuracy being unknown, $V$ is assumed unknown and constant over time. The evolution variance ($W_t$) is estimated using a discount factor $\delta$. For each step $t$, the system variance $W_t$ is defined as a fixed proportion of the model variance $C_t$, such as:

$$P_t = G_t C_{t-1} + G_t^T$$  
$$W_t = \frac{1-\delta}{\delta} P_t$$ (7) (8)

The model is initialized by means of reference analysis: the first observations of the time series are used to estimate the posterior distributions after a first period. Missing observations may occur 1) because a sow did not visit the feeding station during a feeding cycle or 2) because of technical problems at the ESF. As mentioned in Section 4.1, when a sow was not registered at the ESF during a feeding cycle, the value of the response variable was set to: $O_t = \log(N_t)$. In the case of a missing value due to technical problems, the posterior distributions were set equal to the priors, so that on day $t$, the forecast errors from the model $e_t = O_t - f_t$, i.e. difference between the observation and the model forecast $f_t$, equal zero.
External information was included in the model: a model *intervention* was performed each time a subgroup entered or left a group or both. For that purpose, the evolution variance was increased by setting a lower discounting value at the day of intervention, so that the model adapted more rapidly to the new observation (West and Harrison, 1997, chap. 11).

2.2.3. Estimation of the evolution variance
The estimation of the discount factor (and thus the evolution variance, $W_t$) was based on time series of eating rank from 300 sows (100 sows in each of the three herds), which satisfied the following criteria:
• The sows were inserted in the group maximum 10 days after mating
• The sows stayed in the same group during the entire gestating period
• The sows were registered at the ESF for a minimum of 90 days
• The sows were neither observed in oestrus nor treated for lameness/disease(s) during the period

For practical modeling, discount factors in the range of 0.8 to 1 are usually suggested (West and Harrison, 1997). For the purpose of intervention however the model must be able to rapidly adapt to the new observation. For a group of sows, the discount factors used when a subgroup is inserted ($\delta_{in}$), taken out ($\delta_{out}$) or both ($\delta_{in|out}$) must have the possibility to reach lower values than the one used without intervention. Thus, in total, 4 discount factors ($\delta$, $\delta_{in}$, $\delta_{out}$, $\delta_{in|out}$) must be estimated.

The principle behind the estimation is to find the combination of discount factors minimizing the MSE, i.e. the mean sum of squares of the forecast errors $e_t$ of the model. In practice, $\delta$ was varied in the range [0.8, 1.0] by steps of 0.001, while $\delta_{in}$, $\delta_{out}$ and $\delta_{in|out}$ are varied in the range [0.008, 0.8] by steps of 0.088. In total, this leads to 200,000 combinations of values for $\delta$, $\delta_{in}$, $\delta_{out}$ and $\delta_{in|out}$. Since we have 100 sows in each of the three herds, it means that the estimation procedure involves calculation of forecast errors for 60 million time series. Table 3 shows the values of the optimized discount factors for the three herds.

When subgroups both enter and exit a group the same day, the value of the intervention discounting ($\delta_{in|out}$) is similar to the discount factor used in normal conditions ($\delta$), i.e. for the days without group mixing ($\delta$). This may be explained by the fact that the entering subgroup took the place of the subgroup leaving the group.

Figure 2 (a) shows the time series of observations (dots) for the individual eating rank of sow number 44 (herd 1) and the model forecasts (plain) for the whole gestation period.
Vertical lines indicate when subgroups are inserted, or exit a group. Figure 2 (b) shows the evolution of the adaptive coefficient of the DLM (West and Harrison, 1997, p. 38, 42) at the days of intervention: the increase of the adaptive coefficient at the intervention days indicates that the new observation is given more weight; the evolution variance is increased by means of a smaller discounting, which allows the model to adapt quicker to the new observation.

2.3. Detection method
The detection method consists in applying a V-mask (Montgomery, 1997) on the cumulative sum (cusum) of the forecast errors from the model $e_t$, standardized with respect to their variance $Q_t$, such as $u_t = e_t/\sqrt{Q_t}$. The cusum, $c_t$, of the standardized errors $u_t$ is calculated as:

$$c_t = \sum_{i=1}^{t} u_i$$

(9)

In normal conditions, the standardized forecast errors are randomly distributed around zero. It is expected that when a sow presents a specific condition (oestrus, lameness or other health disorders), the deviations between the model forecasts and the observations become wider, so that the cusum tends to drift upwards or downwards. The next section presents the method implemented to catch these deviations.

2.3.1. The V-mask
Figure 3 shows a typical V-mask. The V-mask is directly applied on the cusum with the point $O$ on the last value of $c_t$ and the line $OP$ parallel to the horizontal axis. The V-mask is applied to each new point on the cusum chart and the arms extend backward to the origin. If all the previous cumulative sums, $c_1, c_2, \ldots, c_{t-1}$ lie within the two arms of the V-mask, the process is considered to be 'in-control'; if any of the cumulative sums lies outside the arms of the mask, the process is considered 'out-of-control' and an alarm is given; the value of the cusum is reset to zero each time an alarm is given.

The performance of the V-mask is determined by the lead distance $d$ and the angle $\Psi$ (Figure 3 (a)). The parameters are estimated as:

$$\Psi_t = \tan^{-1}\left(\frac{\Delta}{2A}\right) \quad \text{and} \quad d = \left(\frac{2}{\delta^2}\right)\ln\left(\frac{1-\beta}{\alpha}\right)$$

(10)

where $\alpha$ is the probability of detecting a shift when the process is in control (false positive) and $\beta$ is the probability of not detecting a shift (false negative) of size $\delta$. An implementation of the V-mask is presented in Madsen and Kristensen (2005); the authors
suggest the following values: \( \alpha = 0.01, \beta = 0.01, \Delta = 1.5 \) and \( A = 1 \), which imply a lead distance \( d \approx 4 \) and an angle \( \Psi = 37^\circ \).

2.3.2. Optimization of V-mask parameters

The detection method aims at producing alarms for sows presenting 1) oestrus, 2) lameness and 3) other health disorders. Recordings of these respective states at the herds provide days of reference for optimizing the V-mask parameters; the optimization is based on times series from 300 sows chosen at random, but including individuals presenting both oestrus, lameness or other health disorders.

The initial parameters are set as in Madsen and Kristensen (2005); only the parameters \( \Delta \) and \( A \) are optimized. Different values for \( \Delta \) and \( A \) are tested, allowing values of \( d \) in the range \([1,9]\) and \( \Psi \) in \([24^\circ, 44^\circ]\). An alarm from the V-mask is classified as True Positive (TP) when it occurs during the following reference periods:

• For oestrus: from 3 days before, to 1 day after the observation
• For lameness: from 6 days before, to the day of observation
• For other health disorders: from 3 days before, to 3 days after the observation

An alarm produced outside these reference periods is considered as False Positive (FP). A reference period when no alarm is given is considered as False Negative (FN), and a period with no recording and no alarm is classified as True Negative (TN).

The criteria selected for assessing the method performance were sensitivity, specificity and error rate (Cornou, 2006): sensitivity = \( TP/(TP+FN) \); specificity = \( TN/(TN+FP) \); error rate = \( FP/(FN+TP) \). For practical application, it was assumed that monitoring the three states would require that the detection method helps detecting at least 50% of the sows presenting the various conditions. Therefore, the V-mask parameters were optimized so that the sensitivity is at least 50% and the number of FP is minimum.

Table 4 shows the V-mask parameters after optimization for the three states. Parameters for detecting any of the three states (All) with a single V-mask were also optimized. The angle \( \Psi \) ranged from \( 25.8^\circ \) and \( 27.1^\circ \) according to the herd and the condition detected. These angles are more closed than the one suggested by Madsen and Kristensen (2005); this observation indicates that a given condition (oestrus, lameness or others) will be detected quicker. The optimized leading distances show a larger range and depend heavily on the herd and observed condition.

A lack of recorded states hindered the optimization of the parameters for other health disorders for herd 1 and lameness for herd 3. These parameters were assigned the values of optimized parameters for lameness (herd 1) and other health disorders (herd 3) respectively.
Figure 4 illustrates the implementation of the detection method for sow 44 (see also Figure 2). The alarms catch abrupt drifts of the cusum, i.e. sudden wide deviations between observations and forecasts from the model; the value of the cusum is reset to zero after each alarm given by the V-mask. A first alarm (day 19) is produced three days before the sow is observed in oestrus (day 22), and afterwards at day 45, 64 and 65.

3. Results
Table 5 shows the performance of the detection method for detecting oestrus, lameness and other health disorders for the three herds; the total number of days monitored are 55851, 111891 and 141094, respectively, for herds 1, 2 and 3. Each state was detected using the according V-mask parameters (Table 4) and each time series was modeled using intervention discounting if relevant (Table 3).

Results indicate that sensitivity ranged from 59% to 75% for oestrus detection, from 41% to 70% for lameness and from 0% to 75% for detecting other health disorders. To put these results in perspective, alarms provided by the detection methods are compared to alarms given when the list of sows that have not eaten is used. Using the lists of sows in herds 1, 2 and 3, the sensitivity for oestrus detection is 9%, 20% and 50% (less than 5 observations), 39%, 32% and 22% for lameness detection and 71% (less than five observations) 34% and 16% for detecting other health disorders.

The results in terms of sensitivity are generally higher for the detection method developed here than when the list of sows is used. The major drawback of the detection method is a large number of false alarms, which is higher than false alarms provided by the list of sows: for oestrus detection, the number of false positives observed in herds 1, 2 and 3 is 3634, 21291 and 6466, vs. 1354, 6884 and 3609 when the list of sows was used.

The use of a single V-mask for detecting the three conditions (parameters All in Table 4) was tested for the three herds. A Pearson’s Chi-square test was made to assess whether the performances differ compared to the use of each states’ respective V-mask parameters. For herd 3 sensitivity, specificity and error rate did not differ significantly. For herd 1, only specificity was significantly different, for the three conditions ($p < 0.001$). For herd 2, however, only sensitivity and error rate for oestrus detection were non-significant; the other results differ ($p < 0.001$). The use of a single V-mask for detection of the three conditions does not appear relevant; only half the performances were similar (non significant) when the two methods are compared.

4. Discussion
A method is implemented for detecting oestrus, lameness and other health disorders for group housed sows fed by ESF. The individual eating rank is modeled using a dynamic linear model; deviations between the model forecast and the observations are monitored using a V-mask control chart. After optimization of the V-mask parameters, specific alarms are given for oestrus, lameness and other health disorders.

Results indicate that the detection method allows detection of sows in oestrus with a sensitivity ranging from 59 to 75%. Compared to other results obtained with either the list of sows that have not eaten obtained by the ESF (currently the only kind of alarm system for the farmer) or with a Multi Process Kalman filter (MPKF) as tested by Søllested (2001), the performance of the automatic detection method developed in this paper appears satisfying; the sensitivity for these other methods was 9 to 20%, and below 2% respectively.

However, the number of false alarms given by the detection method was too high. A possible explanation for the high number of false alarms is the fact that oestrus is a rare event to monitor: during the implementation of the method in the three herds, only 81 sows showed oestrus, out of the 308836 days of monitoring. Suggestions for improving the results for automatic oestrus detection are: 1) a reduction of the period for automatic oestrus detection, as implemented for cows (de Mol et al., 1997). For practical application, information from ultrasound scanning performed for diagnosing pregnancy (24 to 38 days after mating) could be included in the model; considering that a sow cannot be in oestrus the first 14 days after mating (day 0), the period for automatic oestrus detection could be limited from day 14 to day 38; only sows with a doubtful pregnancy test should be automatically monitored until a new pregnancy test is performed. Another suggestion for improving automated oestrus detection would be 2) to include a sensitive period in the detection model, as done in Søllested (2001), where the likelihood of a sow being in oestrus was 12.5 greater in the interval day 18-22. To assess whether this suggestion would improve the results, three sensitive periods were tested: day 21, day 20-22 and day 19-23. Due to a too low number of sows registered as in oestrus during these periods, only herd 2 was tested: results indicate that the error rate was reduced by 0.3% only. The sows registered by the herd’s employees as being in oestrus were: 5, 15 and 25%, for the three periods. Søllested (2001) indicates that in normal conditions, 80% of the sows to be mated should be included in the sensitive period day 18-22; it can therefore be questioned whether all sows showing oestrus were correctly registered. More reliable reference days should be used in order to improve accuracy of the detection method; hormonal sampling (progesterone test for instance) may be used to confirm that ovulation has occurred.
The detection method for lameness and other health disorders shows a sensitivity ranging from 41 to 70%, compared to 22 to 39% when the list of sows from the ESF was used as alarm. As for oestrus detection, a major drawback of the method is a too high number of false alarms. A suggestion for reducing the number of false alarms is to broaden the reference periods in which sows with lameness and other health disorders were observed at the herd; the reference period used in this experiment was from 6 days before up to the day of observation (lameness), and from 3 days before to 3 days after the observation (other health disorders). The justification for the choice of the reference period for other health disorders was that individual eating behaviour may not be influenced so drastically in the case of, for instance, vulva biting. For dairy cows, de Mol et al. (1997) suggest a reference period of 7 days before to 7 days after the observation of other health problems than mastitis; a broader reference period should be tested in attempt to improve the method’s performance. Besides, it can be argued that a sow presenting health disorders is expected to decrease in eating rank; detection of deviations in one side only, i.e. downward drift of the eating rank, may help reduce the number of false positives. A control chart such a Tabular Cusum (Montgomery, 1997), which allows monitoring separately upwards and downwards drifts of model deviations, may be used for this purpose.

In this study, the average daily visits per sow indicate a stable eating pattern: 3.0, 2.6 and 3.2 for herds 1, 2 and 3, compared to 7.2 reported by Søllested (2001). The high percentage of sows eating their entire daily ration at the first visit (95.3, 93.5 and 79.5%) is in accordance with Eddison and Roberts (1995); these last authors reported that 79% of all sows ate more than 95% of their daily feeding ration at their first visit at the ESF. This further supported the argument of excluding the number of visits at the ESF for modeling individual eating behaviour.

The detection method suggested in this article is based on monitoring the individual eating rank of group housed sows. The eating rank is selected due to its characteristic stability over a short period of time (Edwards et al., 1988; Bressers, 1993) as well as its interest in directly including information about the group size; this information is modeled in a single time series for each sow. An alternative model is to use both information (eating rank and the group size) in two separate time series, which are aggregated in a multivariate model based on covariances. However, the complexity of this kind of multivariate model as well as the variation of group sizes over time in dynamic groups limit its interest for practical application. On the other hand, a model including information about the eating hierarchy of an entire group would allow better predictions within subgroups; information about the age and size of sows could be used for the purpose (Hunter et al., 1988; Connell et al., 2003).
In the DLM presented in this article, model interventions are performed in order to include information about insertion and/or exclusion of subgroups within a group. Intervention consists in temporarily decreasing the value of the discount factor, to allow the model to adapt quicker to the new observation, and limit a drift of the cumulative sum of forecast errors responsible for alarms. Intervention is performed the same day as the structure of a group was modified; Arey and Edwards (1998) cite Oldigs et al. (1992) and Putten and de Burgwal (1990), who report that the number of aggressions after group mixing stabilizes 3 and 10 days after introduction of new sows in a group, respectively.

The duration of intervention discounting, limited to a single day in this experiment, may have prevented observation of effects of group mixing: even though all herds were found to be affected when a subgroup exits a group, only herd 2 was affected by insertion of a subgroup. Therefore, a longer period of intervention should be tested; however, a too long intervention risks covering possible changes in individual eating rank. For instance, lameness caused by fights for rank attribution may not be detected because of the faster model adaptation in this intervention period.

To improve both the sensitivity and the specificity of the detection method, it is suggested to include a larger number of variables. For dairy cows, de Mol et al. (1997) suggest a multivariate model including five response variables for detecting oestrus and health disorders. For group housed sows fed by ESF, the daily feed consumption could provide information both for detecting oestrus and health disorders (Søllested, 2001; Forbes, 1995; Friend, 1973); ear based temperature (Bressers et al., 1994; Geers et al., 1996) or body activity (Bressers et al., 1993b; Cornou and Heiskanen, 2007) are also potential additional variables. Tasch and Rajkondawar (2004) and Pastell et al. (2006) present a method for detecting lameness for dairy cows, by measuring leg pressure using force sensors; such a method may also be considered for detecting lameness for group housed sows, for instance, when sows are at the ESF. An alternative model, where detection of abnormal states is built-in is the Multi Process Kalman Filter (MPKF) (Thysen, 1993; Søllested, 2001); a MPKF consists of parallel models, each with specific parameters, for a given time series; one of the models, which refers to outliers, can be used to produce alarms, instead of the V-mask, for instance. A drawback of this kind of model is that it is based on the last observation only, and may not be apt to detect a gradual change of the individual eating behaviour, as it may occur for oestrus or health problems; this may explain the very low sensitivity reported by Søllested (2001).

5. Conclusion
The detection method suggested in this article shows a sensitivity that ranges from 39 to 75% according to the condition detected, i.e. oestrus, lameness or other health disorders. Results indicate that the detection method performs generally better than when the list of sows that have not eaten (provided by the ESF and only current tool available to the
farmer) is used as alarms. The major drawback of the detection method for the three conditions is a too high number of false alarms. Measurement of the individual eating rank appears a relevant response variable, since it includes information on the group size. However, models including covariance may help to model more accurately interactions between individual and group eating rank. To improve the performance of the method, it is suggested to reduce the monitoring period (for oestrus) and to include more variables such as body activity or temperature (for all conditions).

6. Acknowledgements
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References


Table 1. Characteristics of the herd management, average (standard deviation), for the three experimental herds. Herd 1 had some pens with 1 electronic sow feeder (ESF) and some with 2.

<table>
<thead>
<tr>
<th></th>
<th>Herd 1</th>
<th>Herd 2</th>
<th>Herd 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sows in the gestation house</td>
<td>350 (11)</td>
<td>1386 (37)</td>
<td>523 (32)</td>
</tr>
<tr>
<td>Group size</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>1 ESF:</td>
<td>62 (5)</td>
<td>129 (26)</td>
<td>50 (14)</td>
</tr>
<tr>
<td>2 ESF:</td>
<td>123 (8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sows introduced in a group</td>
<td>9.1 (8.1)</td>
<td>28.0 (37.0)</td>
<td>41.3 (64.1)</td>
</tr>
<tr>
<td>Sows taken out from a group</td>
<td>8.3 (7.4)</td>
<td>17.7 (14.1)</td>
<td>8.1 (17.6)</td>
</tr>
</tbody>
</table>
Table 2. Use of the electronic sow feeders (ESF), average (standard deviation), for the three experimental herds.

<table>
<thead>
<tr>
<th></th>
<th>Herd 1</th>
<th>Herd 2</th>
<th>Herd 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sows per ESF per day</td>
<td>61.6 (4.32)</td>
<td>64.7 (13.2)</td>
<td>59.7 (21.0)</td>
</tr>
<tr>
<td>Visits per ESF per day</td>
<td>186.4 (52.2)</td>
<td>171.0 (49.4)</td>
<td>191.5 (59.0)</td>
</tr>
<tr>
<td>Feeding visits per ESF per day</td>
<td>63.0 (6.7)</td>
<td>67.0 (15.5)</td>
<td>59.7 (21.0)</td>
</tr>
<tr>
<td>Perc. of sows eating their</td>
<td>95.3 (6.4)</td>
<td>93.5 (13.8)</td>
<td>79.5 (20.5)</td>
</tr>
<tr>
<td>entire ration at first visit</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3. Value of the optimized discount factors ($\delta$) and respective mean squared errors (MSE) for the three herds.

<table>
<thead>
<tr>
<th></th>
<th>Herd 1</th>
<th>Herd 2</th>
<th>Herd 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_{in}$</td>
<td>0.813</td>
<td>0.204</td>
<td>0.906</td>
</tr>
<tr>
<td>$\delta_{out}$</td>
<td>0.461</td>
<td>0.644</td>
<td>0.114</td>
</tr>
<tr>
<td>$\delta_{in} / \delta_{out}$</td>
<td>0.813</td>
<td>0.996</td>
<td>0.906</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.813</td>
<td>0.996</td>
<td>0.906</td>
</tr>
<tr>
<td>MSE</td>
<td>0.113</td>
<td>0.763</td>
<td>0.790</td>
</tr>
</tbody>
</table>
Table 4. Estimated V-mask parameters used to detect the three respective conditions and any of the three conditions (All), for the three herds.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Herd 1</th>
<th></th>
<th>Herd 2</th>
<th></th>
<th>Herd 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\Psi$</td>
<td>d</td>
<td>$\Psi$</td>
<td>d</td>
<td>$\Psi$</td>
<td>d</td>
</tr>
<tr>
<td>Oestrus</td>
<td>25.8</td>
<td>3.2</td>
<td>25.8</td>
<td>1.7</td>
<td>25.8</td>
<td>4.7</td>
</tr>
<tr>
<td>Lameness</td>
<td>27.1</td>
<td>4.1</td>
<td>25.8</td>
<td>6.4</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Other</td>
<td>-</td>
<td>-</td>
<td>25.8</td>
<td>4.7</td>
<td>25.8</td>
<td>4.7</td>
</tr>
<tr>
<td>All</td>
<td>25.8</td>
<td>1.5</td>
<td>25.8</td>
<td>3.6</td>
<td>25.8</td>
<td>4.7</td>
</tr>
</tbody>
</table>
Table 5. Performance of the automatic detection method for detecting oestrus, lameness (Lam.) and other health disorders (Other), using the corresponding V-mask parameters for the three herds.

<table>
<thead>
<tr>
<th></th>
<th>Herd 1</th>
<th></th>
<th>Herd 2</th>
<th></th>
<th>Herd 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Oestrus</td>
<td>Lam.</td>
<td>Other</td>
<td>Oestrus</td>
<td>Lam.</td>
<td>Other</td>
</tr>
<tr>
<td>TP</td>
<td>10</td>
<td>5</td>
<td>0</td>
<td>42</td>
<td>78</td>
<td>93</td>
</tr>
<tr>
<td>TN</td>
<td>52203</td>
<td>51549</td>
<td>51548</td>
<td>90539</td>
<td>89720</td>
<td>88326</td>
</tr>
<tr>
<td>FP</td>
<td>3634</td>
<td>4296</td>
<td>4305</td>
<td>21291</td>
<td>22059</td>
<td>23440</td>
</tr>
<tr>
<td>FN</td>
<td>7</td>
<td>4</td>
<td>1</td>
<td>18</td>
<td>33</td>
<td>31</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.588</td>
<td>0.556</td>
<td>0</td>
<td>0.700</td>
<td>0.703</td>
<td>0.750</td>
</tr>
<tr>
<td>Specificity</td>
<td>0.935</td>
<td>0.923</td>
<td>0.923</td>
<td>0.810</td>
<td>0.803</td>
<td>0.790</td>
</tr>
<tr>
<td>Error rate</td>
<td>0.997</td>
<td>0.999</td>
<td>1.000</td>
<td>0.998</td>
<td>0.996</td>
<td>0.996</td>
</tr>
</tbody>
</table>

*TP: true positive; TN: true negative; FP: false positive; FN: false negative*
Figure captions

Figure 1. Evolution of the eating rank over the gestation period, for sow 330 from herd 1 (a1 and a2) and sow 1642 from herd 3 (b1 and b2), before (a1 and b1) and after (a2 and b2) logarithmic transformation of the individual eating rank; vertical lines indicate when sows enter (dotted, grey), exit (dotted, black) or both enter and exit the group (plain, black).
Figure 2. Modeling of the individual eating rank over the whole gestation period for sow 44 (herd 1). (a) Observation data (dots) and model forecasts (plain); (b) Evolution of the adaptive coefficient. Vertical lines indicate when subgroups enter (dotted, grey), exit (dotted, black) or both enter and exit the group (plain, black).
Figure 3. The cumulative-sum control chart. (a) The V mask and scaling. (b) The cumulative-sum control chart in operation.
Figure 4. Implementation of the V-mask control chart on the cumulative sum of the standardized errors during the gestation period of sow 44 (herd 1); cumulative sum before (plain) and after (dashed) implementation of the V-mask. Vertical lines: recording of the onset of oestrus (black) and alarms given by the V-mask (grey).