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(54) **Title:** MODEL FOR CLASSIFYING AN ACTIVITY OF AN ANIMAL

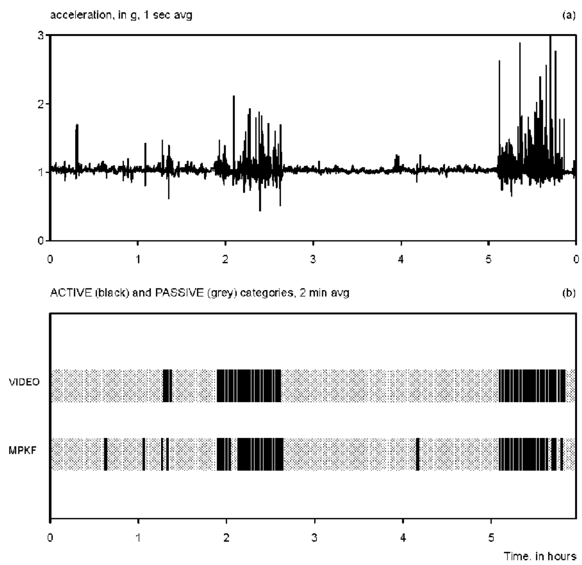

Fig. 4

(57) **Abstract:** The present invention relates to a method for preparing a model for classifying an activity type of a farm animal comprising providing a farm animal with an acceleration sensor; recording data for acceleration over time in dimensions x, y and z from the acceleration sensor; observing the farm animal; synchronising with respect to time the observation of the farm animal with the data from the acceleration sensor; defining an activity type for the farm animal; classifying the activity of the farm animal from the observation of the farm animal according to the defined activity type during a period of time; applying the data from the acceleration sensor obtained during the period of time to prepare the model, comprising an observation equation correlating an observational vector Y_t with a regressor matrix F_t^T, a latent process vector θ_t, and a system equation defining the evolution of the latent process vector.

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Model for classifying an activity of an animal

Field of the invention

The present invention relates to a method for preparing a model for classifying an activity type of a farm animal. In the method a model is prepared from data obtained from an acceleration sensor and synchronising the data with an observation of the farm animal. The data from the acceleration sensor corresponding to an activity type defined from the observation is applied in a multivariate model. The invention also relates to a method of classifying the activity of a farm animal according to a defined activity type using the model and a system for automatically classifying the activity type of a farm animal.

Background of the invention

Automatic monitoring of animal behavior in livestock production opens up possibilities for on-line monitoring of, among others, oestrus, health disorders, and animal welfare in general. Sensor based systems, for which a sensor is attached to the animal, appear particularly suitable for animals housed in large groups or for extensive systems. Such systems should allow quick intervention when a behavioral change is observed.

Measurement of the general activity level, by means of infrared sensors or accelerometers, has been mostly used for oestrus detection, both in dairy and swine production (see, e.g. Firk *et al.,* 2002; Cornou, 2006 for reviews). Monitoring of behavior, either as general categories, such as 'active' vs. 'inactive' or particular activities is also reported. For dairy cows, ALT-pedometers can inform about two categories of behavior: activity is measured by an analogue piezo-sensor and lying time by a digital position sensor (Brehme *et al.,* 2008). Cangar *et al.* (2008) used image analysis to monitor locomotion and posture of pregnant cows. For a period of 24 h before calving, results indicate that on average, 85% of standing and lying and 87% of eating and drinking behavior were correctly classified (n = 8). For sheep in extensive system, Umstatter *et al.* (2008) measured activity data using tilt sensors. Data analysis was performed using three classification methods: a linear discriminant analysis, a classification tree method and a manually developed decision tree. They reported that all methods correctly classified two behaviour categories, 'active' and 'inactive', in 90% of the cases. For swine production, infrared photocell (Erez and Hartsock, 1990; Oliviero *et al.,* 2008) mounted on farrowing crates and force sensors (Oliviero *et al.,* 2008) have been used to study changes in sow's body postures (lying down or standing up) prior to parturition. In animal husbandry, Dynamic Linear Models (DLM) have been used among other things for monitoring cell counts for dairy cattle (Thysen, 1993) or drinking behavior of young pigs (Madsen *et al.,* 2005). In a previous experiment, Cornou and Lundbye-Christensen (2008) used a Multi-Process Kalman Filter (MPKF) to classify five types of activities for group-housed sows. The series included values for the three axes corresponding to the vertical, horizontal and sidewise acceleration. Each series were modeled using a univariate DLM with cyclic components. Results showed that feeding and lying sternally/laterally were best recognised, while walking and rooting were mostly recognised by one particular axis. The authors suggested to explore the use of a multivariate model combining the three axes. It was also discussed to use more general categories, such as 'active behaviour' (feeding, walking, rooting) and 'passive behavior' (lying sternally and laterally) in a larger data set.

The models of Cornou and Lundbye-Christensen (2008), however, did not provide sufficiently good results to classify the activity of the sows. In particular, the models of Cornou and Lundbye-Christensen (2008) did not allow the onset or occurrence of physiological events to be derived from the classification. Thus, the problem remains to define a model to classify the activity of a farm animal with the intention to classify or predict, using the model, the onset or occurrence of a physiological status of a farm animal, such as oestrus in a sow.

The aim of the present invention is to further develop the method to classify the activity of a farm animal by applying multivariate models on data from an acceleration sensor. In particular, it is an aim to improve the results of activity classification, both in terms of sensitivity and specificity. Potential application of this method may be foreseen in the development of monitoring systems that automatically detect behavioral changes, as it may occur, e.g. at the onset of oestrus or at farrowing.

Summary of the invention

The present invention relates to a method for preparing a model for classifying an activity type of a farm animal. The method comprises the steps of providing a farm animal with an acceleration sensor; recording data for acceleration over time in dimensions x, y and z from the acceleration sensor; observing the farm animal; synchronising with respect to time the observation of the farm animal with the data from the acceleration sensor; defining an activity type for the farm animal; classifying the activity of the farm animal from the observation of the farm animal according to the defined activity type during a period of time; applying the data from the acceleration sensor obtained during the period of time to prepare the model, which comprises

an observation equation

$$Y_t = \begin{pmatrix} x_t \\ y_t \\ z_t \end{pmatrix} = F_t^T \theta_t + v_t, \qquad v_t \sim N(0, V)$$

correlating at time t an observational vector $Y_t = \begin{pmatrix} x_t \\ y_t \\ z_t \end{pmatrix}$ of data for dimensions x, y and z with a regressor matrix F_t^T, a latent process vector θ_t and an observational variance V;

a system equation

$$\theta_t = \theta_{t-1} + \omega_t, \qquad \omega_t \sim N(0, W)$$

defining the evolution of the latent process vector θ_t at time t from the latent process vector θ_{t-1} at time t-1 and an evolution variance W at time t;

wherein the evolution variance W indicates how the underlying mean of the latent process vector varies over time.

In a specific embodiment the latent process vector θ_t is

$$\theta_t = \begin{pmatrix} \mu_t^x \\ \mu_t^y \\ \mu_t^z \\ s_t^x \\ s_t^y \\ s_t^z \\ c_t^x \\ c_t^y \\ c_t^z \end{pmatrix}$$

with $\mu_t^x, \mu_t^y, \mu_t^z$ representing trend coordinates, $s_t^x, s_t^y, s_t^z, c_t^x, c_t^y, c_t^z$ representing cyclic coordinates, and regressor matrix F_t^T is

$$F_t^T = \begin{pmatrix} 1 & 0 & 0 & s_t & 0 & 0 & c_t & 0 & 0 \\ 0 & 1 & 0 & 0 & s_t & 0 & 0 & c_t & 0 \\ 0 & 0 & 1 & 0 & 0 & s_t & 0 & 0 & c_t \end{pmatrix},$$

with $s_t = \sin\frac{2\pi}{T}t$ and $c_t = \cos\frac{2\pi}{T}t$ and with the period T allowing the model to adapt to periodic movements. However, other models are also appropriate. For example, the latent process vector 6_t is not limited to nine dimensions, and it may comprise further coordinates than those indicated, for example an additional set of coordinates for each of the three axes z, y, and z. If the latent process vector 6_t includes further coordinates the regressor matrix F_t^T will include a number of columns corresponding to the number of coordinates in the latent process vector 6_t. Likewise, the components s_t and c_t of the regressor matrix F_t^T are not limited to the indicated dependencies on t and T.

In a specific embodiment the evolution variance w has the form

$$w = \begin{bmatrix} W_x^{\mu} & W_{xy}^{\mu} & W_{xz}^{\mu} & W_{xx}^{\mu s} & W_{xy}^{\mu s} & W_{xz}^{\mu s} & W_{xx}^{\mu c} & W_{xy}^{\mu c} & W_{xz}^{\mu c} \\ . & W_y^{\mu} & W_{yz}^{\mu} & W_{yx}^{\mu s} & W_{yy}^{\mu s} & W_{yz}^{\mu s} & W_{yx}^{\mu c} & W_{yy}^{\mu c} & W_{yz}^{\mu c} \\ . & . & W_z^{\mu} & W_{zx}^{\mu s} & W_{zy}^{\mu s} & W_{zz}^{\mu s} & W_{zx}^{\mu c} & W_{zy}^{\mu c} & W_{zz}^{\mu c} \\ . & . & . & W_x^{s} & W_{xy}^{s} & W_{xz}^{s} & W_{xx}^{sc} & W_{xy}^{sc} & W_{xz}^{sc} \\ . & . & . & . & W_y^{s} & W_{yz}^{s} & W_{yx}^{sc} & W_{yy}^{sc} & W_{yz}^{sc} \\ . & . & . & . & . & W_z^{s} & W_{zx}^{sc} & W_{zy}^{sc} & W_{zz}^{sc} \\ . & . & . & . & . & . & W_x^{c} & W_{xy}^{c} & W_{xz}^{c} \\ . & . & . & . & . & . & . & W_y^{c} & W_{yz}^{c} \\ . & . & . & . & . & . & . & . & W_z^{c} \end{bmatrix}$$

with the dots indicating that the matrix is symmetrical, and with the components $W_{subscript}^{superscript}$ of the evolution variance matrix w describing the variance between the axes indicated with the subscript and between the components of the latent process vector 6_t as indicated with the superscript. Other forms of evolution variance matrix W are:

$$W = \begin{bmatrix} W_x^\mu & W_{xy}^\mu & W_{xz}^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & W_y^\mu & W_{yz}^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & W_z^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & . & W_x^s & W_{xy}^s & W_{xz}^s & 0 & 0 & 0 \\ . & . & . & . & W_y^s & W_{yz}^s & 0 & 0 & 0 \\ . & . & . & . & . & W_z^s & 0 & 0 & 0 \\ . & . & . & . & . & . & W_x^c & W_{xy}^c & W_{xz}^c \\ . & . & . & . & . & . & . & W_y^c & W_{yz}^c \\ . & . & . & . & . & . & . & . & W_z^c \end{bmatrix}$$

or

$$W = \begin{bmatrix} W_x^\mu & W_{xy}^\mu & W_{xz}^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & W_y^\mu & W_{yz}^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & W_z^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & . & W_x^s & W_{xy}^s & W_{xz}^s & W_{xx}^{sc} & W_{xy}^{sc} & W_{xz}^{sc} \\ . & . & . & . & W_y^s & W_{yz}^s & W_{yx}^{sc} & W_{yy}^{sc} & W_{yz}^{sc} \\ . & . & . & . & . & W_z^s & W_{zx}^{sc} & W_{zy}^{sc} & W_{zz}^{sc} \\ . & . & . & . & . & . & W_x^c & W_{xy}^c & W_{xz}^c \\ . & . & . & . & . & . & . & W_y^c & W_{yz}^c \\ . & . & . & . & . & . & . & . & W_z^c \end{bmatrix}$$

Alternatively, the evolution variance matrix W may assume independence so that it takes the form :

$$W = \begin{bmatrix} W_x^\mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ . & W_y^\mu & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & W_z^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & . & W_x^s & 0 & 0 & 0 & 0 & 0 \\ . & . & . & . & W_y^s & 0 & 0 & 0 & 0 \\ . & . & . & . & . & W_z^s & 0 & 0 & 0 \\ . & . & . & . & . & . & W_x^c & 0 & 0 \\ . & . & . & . & . & . & . & W_y^c & 0 \\ . & . & . & . & . & . & . & . & W_z^c \end{bmatrix}$$

However, the evolution variance matrix W may also take other forms depending on the assumed dependencies between the axes indicated with the subscript and between the components of the latent process vector Q_t.

In another aspect the invention relates to a method of classifying the activity of a farm animal according to a defined activity type, the method comprising : providing a farm animal with an acceleration sensor; recording data for acceleration over time in dimensions x, y and z from the acceleration sensor; applying the data from the acceleration sensor in a model prepared as describe above.

Thus, the invention provides a method for preparing a model for classifying an activity type of a farm animal and method of classifying the activity of a farm animal according to a defined activity type using the prepared model. In general this type of model may be describes as a multivariate Dynamic Linear Model (DLM).

According to the method of the invention for preparing a model a data set is obtained from an acceleration sensor carried by a farm animal; the data set will correspond to a defined activity type which the animal performed when obtaining the data. When the data set has been obtained the coordinates of the latent process vector Q_t may be selected from an initial consideration of expected or known variations or the like. For example, the data may suggest that the data contains a cyclic variation leading to the incorporation in the model of corresponding coordinates, e.g. s_t and c_t of the regressor matrix F_t^T and corresponding coordinates of the latent process vector Q_t. In one embodiment a cyclic variation of s_t and c_t with a period, 7, of 22 seconds was included.

The general DLM is represented by the set of two equations, the observation equation and the system equation as described above. Further details about DLM's are given by West and Harrison (1997). In general, the observation equation defines the sampling distribution for the observation Y_t conditional on an unobservable state vector, the latent process vector Q_t. The system equation defines the time evolution of the state the latent process vector Q_t.

The error sequences v_t and ω_T are assumed to be internally and mutually independent. The DLM combined with a Kalman Filter (KF) (Kalman, 1960) estimates the underlying latent process vector Q_t by its conditional mean vector m_t and its variance-covariance matrix C_t (the model variance) given all previous observations $D_t = \{Y_{l}, \ldots, Y_t\}$ of the acceleration measurements. The conditional distributions of the predictions are

$$(\theta_t|D_t)\sim N(m_t, C_t), \qquad (Y_t|D_{t-1})\sim N(f_t, Q_t)$$

The parameters m_t, C_t, f_t and Q_t are calculated stepwise employing the updating equations of the Kalman Filter:

(a) Posterior for Q_t at time *t-1* :

$$(\theta_{t-1}|\mathrm{V}_{1}) \sim \mathrm{V}(\mathbf{m}_{t-1}, \mathrm{C}_{t-1})$$

(b) Prior for Θ at time t:

$$(\theta_t|D_{t-1}) \sim N(a_t, R_t)$$

where

$$\boldsymbol{a_t} = \boldsymbol{G_t} m_{t-1} \quad \text{and} \quad \boldsymbol{R_t} = \boldsymbol{GtC\wedge G't} + \boldsymbol{W_t}$$

(c) One step forecast for $\boldsymbol{Y_t}$ at time t:

$$(Y_t|D_{t-1}) \sim N(f_t, Q_t)$$

where

$$\boldsymbol{f_t} = F'_t \boldsymbol{a_t} \quad \text{and} \quad \boldsymbol{Q_t} = F'_t \boldsymbol{R_t F_t} + \boldsymbol{V_t}$$

(d) Posterior for Q_t at time t:

$$(\theta_t|D_t) \sim N(m_t, C_t)$$

with updating equations

$$\boldsymbol{m_t} = \boldsymbol{a_t} + \boldsymbol{A_t r_t} \quad \text{and} \quad \boldsymbol{C_t} = \boldsymbol{R_t} - \boldsymbol{A_t Q_t} A'_t$$

where

$$\boldsymbol{A_t} = \boldsymbol{R_t F_t} Q_t^{-1} \quad \text{and} \quad \boldsymbol{r_t} = \boldsymbol{Y_t} - \boldsymbol{f_t}.$$

Further details of the Kalman Filter, the updating equations and the DLM are given in West and Harrison, 1997, chapter 4, in particular section 4.3, and Kalman (1960), which are hereby incorporated by reference.

A model for the activity type of a farm animal is characterised by its activity-specific parameters, the observational variance V and the evolution variance W. The parameters V and W may be estimated using any appropriate algorithm, e.g. likelihood estimation or Bayesian estimation. However, it is preferred that the parameters V and W are estimated using the expectation-maximisation (EM) algorithm as described and generally defined by Dempster *et al.* (1977), or alternatively following the explanation of the use of the EM with state space models of Dethlefsen (2001) or the illustration of the use of the EM with state space models of J0rgensen *et al.* (1996). In short, the EM algorithm uses the conditional mean vector m_t and model variance C_t, as estimated using the updating equations indicated above, and their respective smoothed components $\tilde{\boldsymbol{m}}_t$ and $\tilde{\boldsymbol{C}}_t$. An additional discussion of the specifics of the EM algorithm used in the present context is provided by West and Harrison (1997), chapter 4.7, e.g. p. 113, which are hereby incorporated by reference.

The quality of the model may also be checked in the method of the invention. For example, the quality may be checked regarding the assumption of mutual independence between the error sequences v_t and ω_t as well as other estimated parameters. Model fit may for example be checked analysing the residuals:

$$r_t = Y_t - f_t \sim N(0, Q_t)$$

where f_t is the prediction of Y_t given the past. These residuals may then be standardised with respect to the forecast variance Q_t as

$$f_t = Q_t^{-1/2} r_t \sim N(0, I)$$

For a good model fit, these residuals are mutually independent and normally distributed, e.g. when analysed coordinate-wise.

The model is generally prepared by obtaining data from an acceleration sensor from a farm animal and using this data to prepare the model. For recording the data the farm animal is observed during a period of time when it is performing a defined activity type. Any method of observing the farm animal is appropriate, although it is preferred to observe the farm animal using video recording. The data from the acceleration sensor is synchronised with respect to time with the data from the observation so that the data represents the defined activity. The data from the acceleration sensor may be recorded for a single animal or for a group of animals. It is preferred that data are recorded from more than one animal performing the activity type. However, it is also possible to employ separate data recordings for the same individual animal performing the defined activity type during different periods of time. The data thus obtained and used in the model may also be termed a "learning data set". The model may be validated using a "test data set", which is obtained in the same way as the learning data set.

In another aspect the invention relates to a method of classifying the activity of a farm animal according to a defined activity type using the model. Data obtained from an acceleration sensor fitted on a farm animal may be employed in the model described above using a classification method called a "multi-process Kalman filter" (MPKF) or "multi-process dynamic linear model" of class I. Thus, the activity of a farm animal may be classified as belonging to a defined activity type, so that the acceleration sensor may be used in place of observation of the farm animal. This is advantageous since the data from the acceleration sensor, in the form of values for acceleration in each of the dimensions x, y and z as a function of time, t, are more easily processed by a computer and may therefore be used to automatically classify the activity of a farm animal according to activity type.

Thus, the data from an acceleration sensor is applied to a MPKF algorithm for classification of the activity of the farm animal. Each DLM for a given activity type is characterised by the variance parameters M_t: $\alpha(i) = \{V(i), W(i)\}$ where index i indicates the activity type defined for the model, and where $\alpha(i)$ holds for all t.

Each DLM, M_t (a), is analysed using the updating equations given above. At each time t, the posterior probabilities (p_t) are calculated for each activity type, i, as

$$p_t(i) \propto \varphi_t(i) \times p_{t-1}(i),$$

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

The predictive distribution is

$$\varphi_t(i) = \frac{1}{\sqrt{det2\pi Q_t}} \exp\left(-\frac{1}{2}(Y_t - f_t)^T Q_t^{-1}(Y_t - f_t)\right)$$

Each DLM is analysed using all pairs of variance parameters estimated from the Learning data sets for all defined activity types for which a model has been prepared. For estimating the probability of a given activity type, a uniform distribution for all defined activity types may be used as a starting point in the calculation so that if e.g. five activity types have been modelled the initial values of the probabilities in each case are set to 0.2. However, the initial values of the probabilities are not restricted to a uniform distribution. In certain embodiments knowledge of the typical activity profile may be used to define a different initial value of the probability for that activity compared to other activities. Alternatively, the last observation result of a previous series may be used as initial prior for the next series, or if longer series intervals are used for classifying activity types, a moving window indicating when an activity change occurs could be used.

For validating the models the data from the test data set corresponding to periods of time of an appropriate length, e.g. series of 2 min duration, are analysed as follows: For each observation, the activity type result (observation result) is determined as being the one with the highest posterior probability. (2) Then, for each series, the activity type which has the largest number of observation results is determined as series result.

The methods of the invention are appropriate for any kind of farm animal, although the methods are particularly suited for pigs, for example sows.

Any type of acceleration sensor may be used in the invention, but a digital accelerometer, such as LIS3L02DS from STMicroelectronics, is preferred.

Any kind of activity type may be appropriately modelled and classified in the methods of the invention. In general, two or more activity types will be modelled for a given farm animal, however, it is also possible to define a single activity type and define all other possible activities of a farm animal as "other activity". In certain embodiments of the invention the defined activity type is defined as active or passive. In other embodiments the activity type is defined as feeding (FE), rooting (RO), walking (WA), lying sternally (LS) or lying laterally (LL).

The invention also relates to a method of recording an activity pattern of a farm animal comprising classifying the activity of the farm animal according to the above method over a period of time and recording the activity type(s) of the farm animal during the period of time. Such a pattern may comprise the relative amount of time spent by a farm animal performing a given activity or activities compared to other activities, or the pattern may also comprise specifications of the start, end and duration of a given activity type. Further, the activity pattern may record the number of changes in activity types over the period of time in the pattern. For example, an activity pattern may record when and for how long a farm is feeding. An activity pattern will typically also include a record of time spend by the farm animal not performing the activity type. An activity pattern may comprise a single activity type versus all other activity types, or several activity types may be comprised in the activity pattern. It is also possible to combine or "collapse" several different activity types into a common category, so that for example all modelled activity types representing active activity types are collapsed into a category "active" and all modelled activity types representing passive activity types are collapsed into a category "passive". Likewise, one group of "active" activity types may collapsed into a group of "highly active" activity types, and another into a group of "moderately active" activity types.

An activity pattern may be compared to a normal or otherwise predetermined activity pattern for the type of farm animal, and thereby it can be determined if the activity pattern of the farm animal deviates from the activity pattern normally observed or the predetermined pattern for the type of farm animal. Such deviations may provide an indication of the general welfare status of the farm animal, or the activity pattern may be used to determine a physiological state of the farm animal. For example, the activity pattern may indicate the onset of oestrus, farrowing, illness (fever, lameness etc). Monitoring the activity pattern of a farm animal may also be used to predict the onset of a physiological event, e.g. the onset of a sow's farrowing may be predicted from its activity pattern. Likewise, the monitoring or automatic monitoring may involve monitoring the general health status to detect or predict health disorders occurring e.g. around farrowing. Thus, in another aspect the invention relates to a method for determining the physiological state of a farm animal by recording an activity pattern of a farm animal and comparing the activity pattern to a normal or otherwise predetermined activity pattern for the type of farm animal. In particular, the physiological state may be onset of oestrus, onset of farrowing, or prediction of a health disorder

Specific examples of relations between activity patterns and occurrence of physiological events are given below. However, these are not limiting to the invention and other physiological events may also be monitored via the activity pattern according to the invention.

At the approach of farrowing, sows perform 'nest building behaviour', which is characterised by an increase of the activity type of 'active categories'. Even though confined, the sow attempts to build a nest, and is therefore more active. This behaviour typically starts about 24 hours before the onset of farrowing. This behaviour is well documented, and recent examples of attempt to automatically monitor this behaviour are found in Oliviero *et al.* (2008) and Erez and Hartsock (1990).

The inventors found it possible to detect the onset of farrowing (in average 11 hours before farrowing) using a threshold to monitor increases in the activity type automatically classified as "high active" behaviour using the methods of the invention *(article in preparation).*

At the approach of oestrus, a behaviour called proceptive behaviour, is that the sow will tend to search for the presence of a boar. This as for consequence that the sow will walk more, and be more active, going back and forth to find a boar, and be more restless in general. By using the invention, we can monitor this increase of activity, which can thereby be used to detect the onset of oestrus.

In the case of illness, sows will eat less, and be less active: monitoring 'feeding activity', and general 'active' and 'passive' categories can give alarms in the case of health disorders.

According to the invention the activity pattern may be monitored automatically. For example, a computer or the like may be programmed to monitor the activity pattern of a farm animal, e.g. each individual of a group of farm animals, so that a signal, e.g. an alarm, may be send to the farmer in case of the occurrence of the above events. Thus, in yet another aspect, the invention relates to a system for automatically classifying the activity type of a farm animal, which system comprises

- one or more acceleration sensor boxes each comprising an acceleration sensor, a battery package and appropriate means for wirelessly transmitting data;

- means for wirelessly collecting data from the one or more acceleration sensors;

- a computer readable storage medium containing a model for classifying an activity type of a farm animal according to the first aspect of the invention, and computer program code configured to automatically classify the activity type of a farm animal; and

- a data processor for executing the computer program code.

The computer program code may also be configured to record an activity pattern of a farm animal or to determine the physiological state of a farm animal.

The term "acceleration sensor box" is not intended to include any limitations as to the size or shape of the "box"; the acceleration sensor box may be of any size or shape to contain the acceleration sensor, the battery package and the means for wirelessly transmitting data. However, the acceleration sensor box may also comprise other functionalities, e.g. a GPS-sensor to track the location of the farm animal, means to fit it to a neck collar or ear tag or the like. The acceleration sensor box may also comprise a data storage medium for storing data from the acceleration sensor.

The battery package is likewise not to be considered limiting to the invention but may comprise any unit capable of supplying the acceleration sensor and the means for wirelessly transmitting data with sufficient power. The battery package may contain any conventional non-rechargeable or rechargeable battery, e.g. a Li-ion or Li-polymer battery, or it may comprise other energy storage units, such as a fuel cell, e.g. a direct methanol fuel cell. The battery package may also comprise other functionalities, e.g. a solar cell for recharging a battery.

Any system for wirelessly transferring data between the acceleration sensor and the computer may be employed. Examples of appropriate transfer protocols are Bluetooth, WiFi, mobile phone networks, etc.

The computer readable storage medium will typically be a medium allowing data obtained in the analysis to be stored thereon. Thus, a computer readable storage medium will typically be able to store data obtained from multiple, e.g. 10, 100 or more, acceleration sensors over a period of time, such as 24 hours, a week, a month or even longer. Likewise, the parameters V and W for a model for classifying an activity type of a farm animal will also be stored on the storage medium allowing data to be deleted and replaced so that the parameters may be replaced with a newer, e.g. an improved, model. It is however, also possible that the model is stored on a replaceable storage medium of a "read-only" type so that the read-only storage medium with the model may be replaced with another storage medium with a newer model. The computer readable storage medium may also contain multiple models, e.g. five, representing different activity types.

The data processor for executing the computer program code should be able to process the acceleration data obtained from the one or more acceleration sensors using the computer program code on the storage medium. In particular, the computer program code may be able to record an activity pattern for a farm animal with an acceleration sensor. Further, the system may comprise, e.g. stored on the computer readable storage medium, a normal or otherwise predetermined activity pattern for a farm animal; in this case the computer program code will also be able to compare the activity pattern of the farm animal with the normal or otherwise predetermined activity pattern.

The system may also have a user interface, comprising e.g. a screen or a printer, for presenting the classification of the activity type or the activity pattern of a farm animal when this is recorded. The system may further be able to give a signal, e.g. an alarm, in case of the occurrence of a particular activity pattern representing e.g. the physiological events listed above.

Brief description of the figures

Fig. 1 shows the value of estimated parameters of a multivariate model prepared according to the method of the invention.

Fig. 2 shows posterior probabilities for five activity types using a multivariate model prepared according to the method of the invention.

Fig. 3 shows the result of a MPKF using parameters from a multivariate model prepared according to the method of the invention.

Fig. 4 shows application of a MPKF for a 6 h period for one sow:

(a) sec average of the vector length of acceleration; (b) category classification : video analysis and MPKF results.

Fig. 5. (a) 24 hours time series of acceleration measurements (10 sec average) for sow 1, two days before farrowing. (b) Output resuits (2 min intervals) from the MPKF. HA: High Active; MA: Medium Active; LI : Lying Side 1; L2: Lying Side 2; LS: Lying Sternally.

Fig. 6. (a) 24 hours time series of acceleration measurements (10 sec average) for sow 1, the day of farrowing. (b) Output results (2 min intervals) from the MPKF. HA: High Active; MA: Medium Active; LI : Lying Side 1; L2: Lying Side 2; LS: Lying Sternally.

Fig. 7. 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 (dO 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.

Fig. 8. Daily averaged number of changes of activity type for sows in group S (al) and NS (bl), and daily averaged length (in number of 2 min intervals) used performing the activities for group S (a2) , and NS (b2) : HA (plain line), MA (dashed line) and mean for lying laterally (LI and L2) positions (points). Horizontal axis: 24 hours intervals around farrowing (dO is the last 24h before the onset of farrowing).

Fig. 9. 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 (hO) to 24 hours after: HA (bar plots), MA (plain line) and sum of Lying laterally LI and L2 (points).

Detailed description of the invention

The invention provides a method for preparing a model for classifying an activity type of a farm animal, and further a method of classifying the activity of a farm animal according to a defined activity type using the prepared model. Also comprised in the invention is a method for recording an activity pattern of a farm animal as well as a system for automatically classifying the activity type of a farm animal. The invention will now be described in more detail referring to specific embodiments. In order to more fully explain the invention, definitions of the terms employed in this document are given below.

In the context of the present invention a "farm animal" is any animal, which is relevant in farming, agriculture and the like. Such animals may also be known as "domesticated animals". Examples of farm animals are pigs, cows, sheep, goats, horses, deer, camels, elephants, hens, chickens, ducks, geese, turkeys, etc. Other farm animals are well-known in within the art. It is preferred that the farm animal is a pig, in particular a sow.

The method of the present invention prepares a model for classifying an activity of a farm animal. The term "activity" should be understood broadly and may relate to any kind of behaviour of a farm animal, e.g. a behaviour which may be defined from observing the farm animal. In a basic form, a defined activity may be that a farm animal is "active" or "passive", and these definitions may further include other activities. Thus for example, the activity of a farm animal may also include definitions such as walking, running, rooting, feeding, eating, swimming, climbing, etc. which may be grouped as active activities, or the activity may include definitions such as lying, e.g. lying laterally, lying sternally, sitting, sleeping, standing, resting, perching etc. which may be grouped as passive activities. In general, a model will relate to one activity, e.g. to walking, rooting, feeding, lying laterally, or lying sternally, however, models for certain activities may be joined or "collapsed" into a model containing several activities of the individual models. For example, models for walking, rooting, and feeding may be joined to a model for active activity. It is not necessary to define all possible activities of a farm animal in order to obtain a model for a defined activity. For example, a model for "walking" for a pig may be prepared without considering any other possible activities of the pig. Likewise, a model for "rooting" for the pig may be prepared independently from the model for walking. However, it should be possible to define and differentiate the activities for the farm animal by observing, e.g. visually observing, the farm animal.

In the present invention, the term "model" refers to an algorithm which may classify the activity of a farm animal from data from an acceleration sensor. The model will include knowledge of previous data from the acceleration sensor combined with knowledge of a defined activity, and thereby the model can be said to correlate previous data from an acceleration sensor with current data from the acceleration sensor in order to classify the current activity of the farm animal. The previous data used to prepare the model may be obtained from observation of a single farm animal performing a defined activity and corresponding data obtained from an acceleration sensor fitted to that farm animal, or the data used to prepare the model may be obtained from a group of animals. It is preferred that data and observations used to prepare a model are obtained from a group of animals. The model obtained will generally be specific for a type of farm animal and its defined activity.

The present application employs several symbols in its models and the equations used to estimate the models. These symbols are summarised in the table below with a brief definition; examples for preferred embodiments are provided in the definitions of some symbols. Further the right column of the table lists the dimensions of vectors/matrices in a specific embodiment of the invention.

Symbol	Definition	Dimension
Y_t	Observation vector	3x1
θ_t	Latent process vector	9x1
$\bar{F}_t'$	Regressor matrix	3x9
v_t	Observation error	3x1
ω_t	Evolution error	3x3
D_t	Information at time t	
V	Observation variance	3x3
W	Evolution variance	9x9
W_μ^x	Level component of system variance for axis x	
W_μ^y	Level component of system variance for axis y	
W_μ^z	Level component of system variance for axis z	
s_t	Component, e.g. $\sin \frac{2\pi}{T} t$	

Symbol	Definition	Dimension
c_t	Component, e.g. $\cos\frac{2\pi}{T}t$	
T	Period, e.g. 22 seconds	
θ_0	Initial value for latent process vector	9x1
m_0	Initial value for mean of the latent process	9x1
C_0	Initial value for variance of the latent process	9x9
m_t	Posterior mean of the latent process	9x1
C_t	Posterior variance of the latent process	9x9
a_t	Prior mean	9x1
R_t	Prior variance	9x9
f_t	One step forecast mean	3x1
Q_t	One step forecast variance	3x3
r_t	One step forecast error	3x1
f_t	Standardised One step forecast error	3x1
A_t	Adaptive coefficient	9x3
G_t	System matrix	9x9
fn_t	Smoothed mean	9x1
$\tilde{C}_t$	Smoothed variance	9x9
φ_t	Predictive distribution	
P_t	Posterior probability	

The model prepared according to the method of the invention may be employed to automatically classify a farm animal fitted with an acceleration sensor. In terms of the invention "automatic classification" means that the activity of a farm animal fitted with an acceleration sensor is monitored using a model prepared according to the invention. In general, the activity type will be recorded over a period of time to obtain for the farm animal an activity pattern.

An "activity pattern" is a record of the activity type of a farm animal over time. For example, an activity type may be recorded for a farm animal to describe the relative amount of time the farm animal spends performing the activity type; the activity pattern may also include a record of the specific periods of time, e.g. during a 24 hours period, during a week, a month etc., the farm animal performs the activity. In addition, the duration(s) of an activity type may also be recorded along with the time point for the start and end of the activity type. The activity pattern may also be related to the age of the farm animal, or to a stage in a cycle, such as the reproductive or mating cycle, of a farm animal.

The activity pattern may comprise one or more different activity types obtained using appropriate models for each of the activity types, and the activity pattern may provide knowledge of the animal's status by comparing the activity pattern with a database of known activity patterns. For example, the activity patterns could allow the individual farm animal to be monitored for the full duration of its reproductive cycle, e.g. from the mating section to the farrowing house. Other applications, such as monitoring animal welfare, can also be foreseen.

The main interest of classifying activity types automatically is to supplement (visual) observation with automatic registration. This makes it possible to monitor a larger number of individuals at the same time. Development of a method of automatically classifying activity types is the first step towards further automated methods designed to detect oestrus, farrowing, illness or welfare status. In particular, the data from an acceleration sensor is more easily transferred wirelessly than e.g. a video signal, and furthermore since the acceleration sensor is carried by the farm animal it will not be restricted to be in the field of observation of e.g. a camera or the like in order to obtain data for the farm animal. A further advantage of employing individually carried acceleration sensors is that the individual farm animals are easily differentiated from each other allowing a simple form of monitoring of the individual farm animal.

In terms of the present invention an "acceleration sensor" (or "accelerometer") is any device capable of measuring acceleration in three dimensions (referred to as x, *y* and z). An example of an appropriate acceleration sensor is a digital accelerometer, such as LIS3L02DS from STMicroelectronics. An acceleration sensor should be capable of measuring acceleration several times per second, e.g. four times per second, and the acceleration sensor should further be capable of continuous operation. For example, the acceleration sensor should be capable of measuring data 24 hours a day for e.g. 20 days or more. Thus, the data from the acceleration sensor includes acceleration data for each of the dimensions x, y and z and the corresponding time, t. For example, the acceleration data may be expressed as a vector:

$$Y_t = \begin{pmatrix} x_t \\ y_t \\ z_t \end{pmatrix}$$

with the subscript t denoting the time the acceleration data was obtained.

Acceleration is a vector quantity defining the rate at which velocity is changed, and a farm animal is treated as accelerating if its velocity is changing. With a digital accelerometer, such as the LIS3L02DS, values for the three axes (x, y and z) may be measured in volts. Of these axes, x corresponds to the vertical dimension; y corresponds to the horizontal dimension, with the acceleration being measured sidewise, while z corresponds to the horizontal dimension, with the acceleration being measured forwards. Before further processing, the data may be converted into the acceleration unit (g). When an accelerometer is placed immobile on a plane surface, the acceleration values for the axes x, y and z, are respectively 1, 0 and 0 g (the first value being due to the effect of gravity).

Data from an acceleration sensor may be analysed in a univariate model where data for each axis, i.e. x, y and z, or alternatively the length of the acceleration vector, $acc = \sqrt{x^2 + y^2 + z^2}$, is analysed separately, so that the data from an acceleration sensor may give rise to four seperate and independent models for the same activity of a farm animal. However, the present inventors have now found that when data from an acceleration sensor are analysed in a multivariate model superior results with respect to classification of the activity type of a farm animal can be obtained, compared to data analysed in a univariate model. The model prepared according to the present invention is thus a multivariate model. With "multivariate" is meant that data from more than one axis is considered in a single model. Thus, for example a multivariate model may include data from the x and y axes, the x and z axes, the y and z axes, or all three axes, i.e. x, *y* and z. A multivariate model may also include the length of the acceleration vector, *acc,* or the model may include the length of the acceleration vector in one or more planes, e.g. the *xy*-plane, the xz-plane or the yz-plane. Furthermore, a multivariate model may include any combination of axes or vector lengths in one or more planes.

The multivariate model prepared according to the method of the invention includes the acceleration data recorded for the x, *y* and z axes. The present inventors have found that using the acceleration data recorded for the x, *y* and z axes in a multivariate model may provide a better model, i.e. a model with a higher probability of correctly classifying the activity type of a farm animal, than a multivariate model employing only two axes, or a model also including the length(s) of the acceleration vector as a parameter.

When a farm animal is provided with an acceleration sensor, the acceleration sensor may for example be placed in a box containing a battery package and appropriate means for storing data and/or for wirelessly transmitting data to a computer. Data may be transmitted using any appropriate protocol for wireless data transmission, such as those defined under the IEEE 802.15 standard ("Bluetooth"), e.g. data may be transferred to a PC via an external Bluetooth dongle, or the IEEE 802.11 standard, also known as "WiFi". The acceleration sensor, e.g. in an appropriate box, may be placed anywhere on a farm animal as long as the acceleration sensor can be carried by the farm animal for prolonged periods of time. For example, the acceleration sensor may be fitted on a neck collar which is put on a farm animal. The acceleration sensor may also be fitted to an ear tag, or it may be placed on the back, head, shoulder, leg, etc. of a farm animal. When the acceleration sensor is placed on the head of a farm animal, e.g. as an ear tag, it may provide better wireless transmission of the data from the acceleration sensor to e.g. a Bluetooth dongle, since the farm animal is unlikely to lie on the acceleration sensor.

To prepare the model the farm animal is observed. The observation may be via any appropriate method, e.g. the farm animal may be observed visually, or the observation may be performed using a camera, e.g. a video camera. The term "observing" should not be understood in a limiting way, but will include any way of observing the activity of the farm animal. The observation may thus also comprise recording specific acts performed by the farm animal, such as feding, eating, drinking, defacation, urination or other physiological functions etc. For example, the farm animal may have access to an electronic feeding station capable of registering when, for how long and how much the animal eats, so that the data from the acceleration sensor can be linked specifically to the act of feeding or eating.

It is preferred that the observation is visual and is performed using a video camera, and further it is preferred that the video camera records the time allowing the data from the video camera to be synchronised with data from the acceleration sensor. Thus, by "synchronising" the observation and the data from the acceleration sensor it is possible to synchronise video data corresponding to a defined activity for a specified period of time with data from the acceleration sensor for the same period of time, and thereby obtain data from the acceleration sensor for the defined activity.

In addition, the observation may also involve specific tests to determine the onset or occurrence of a physiological status of a farm animal, so that the data from the acceleration sensor may be linked specifically with this onset or occurrence; as an example oestrus detection in sows may be determined using a specific test. For example, oestrus may be detected by the The Back Pressure Test (BPT) of Willemse and Boender (1966, A quantitative and qualitative analysis of oestrus in gilts. *Tijdschr. Diergeneesk.* 91: 349-362, which is hereby incorporated by reference). This test may be used to identify the time of first and last standing response as a sign of heat at both weaning oestrus (BPTw) and experimental oestrus (BPTe). The BPTw may e.g. be performed three times a day (at 07:00, 14:00 and 21:00) until 24 hours after the sow ceases to show standing response at BPT. The BPTe may be performed three times a day (at 07:00, 14:00 and 21:00) starting 18 days from commencing the BPTw test at 07:00 until 24 hours after the sow ceases to show standing oestrus by BPT. The test may be performed next to a teaser boar. This detection may be performed to identify the exact onset and end of oestrus, and the data from the acceleration sensor may be linked specifically with observations from the BPT to determine the onset of oestrus as compared to the anoestrus period using data from the acceleration sensor in place of the PBT.

Further specific observations may be measurement of temperature, e.g. ear base, vaginal and/or rectal temperature, or vaginal electrical resistance, which may provide indications of e.g. onset of oestrus as explained in section 5.4 (which is hereby incorporated by reference) of C. Cornou, 2007, Automated Monitoring Methods For Group Housed Sows, Ph.D. Thesis, Department of Large Animal Sciences, Faculty of Life Sciences, University of Copenhagen, Denmark.

Feeding behaviour of a farm animal, e.g. a sow, may also provide an indication of onset or occurrence of physiological status, such as oestrus, of the farm animal, and the feeding behaviour may conveniently be monitored using an Electronic Sow Feeder (ESF), see e.g. Cornou, 2007, section 7.2. For example, for modeling purposes the description of feeding behaviour for sows fed by an ESF could include the following elements: the order in which each individual sow accesses the ESF, the group size, the starting time of the daily feeding cycle and the frequency of group mixing. Further details are given in Cornou, 2007, section 7.3 which is hereby incorporated by reference.

Examples

The invention is now described in the following non-limiting examples.

Example 1

1.1. Acceleration measurements

1.1.1. Collection of acceleration measurements

Time series of acceleration measurements referred to in this Example are extracts of data collected for 11 group-housed sows, in a production herd in Denmark. The experimental sows were chosen so that they were all between their third and sixth parity, had no leg disorder and reproduction cycles in prior parities of 145-147 days. They were housed in a dynamic group of approximately 100 sows, had access to two electronic sow feeders and three nipple drinkers. The dimension of the pen was 22.45 m long by 12.45 m wide. Resting areas were straw-bedded and activity areas had solid or slatted floors.

A box containing the accelerometer and the battery package was fitted on a neck collar which was put on each experimental sow. Acceleration data were measured in three dimensions using a digital accelerometer (LIS3L02DS from STMicroelectronics) four times per second, 24 h a day, during 20 days. Data were transferred to two PCs via three Bluetooth dongles which hung from the ceiling.

The sows were video recorded 24 h a day (ten pictures per second) by three wide-angle cameras placed at approximately 5 m above the pen. The time stamps of the video recordings and acceleration measurements were synchronized. The experimental sows were individually marked on their back, and video recordings were used to identify the types of activity they were performing.

1.1.2. Data sets

Five types of activity, similar to the ones used in Cornou and Lundbye-Christensen (2008), were selected : feeding (FE), rooting (RO), walking (WA), lying sternally (LS) and lying laterally (LL). To model and develop a method to automatically classify these activities, two data sets were used : a *Learning* data set was used to estimate the model parameters; a *Test* data set was used to validate the classification method. These data sets include extracts of time series (values for the three-dimensional axes x, *y* and z), corresponding to each of the five activities. The selection of these series' extracts was made with the help of video recordings, and satisfied the following criteria : a given activity fills the entire time series extracts and potential overlapping activities (such as walking and rooting) are reduced to a minimum.

(I) The *Learning* data set includes 46 series of 10 min : 6, 7, 11, 11 and 11 series, respectively for FE, RO, WA, LS and LL; series correspond to 6, 7, 11, 11 and 11 distinct sows, and are from February the 15th 2007.

(II) The *Test* data set includes 490 series of 2 min : 84, 79, 107, 110 and 110, respectively for FE, RO, WA, LS and LL; series correspond to 11, 9, 11, 11 and 11 distinct sows, and are from February the 14th and 17th 2007. The smaller number of series for both feeding and rooting activities is due partly to missing data and to the fact that these types of activities are performed more rarely.

(III) A third, Previous data set, corresponding to the one used in Cornou and Lundbye-Christensen (2008) is used to assess potential improvement of the models and methods as compared to the inventors' previous work. This data set includes 50 series of 2 min observations extracted from 5 sows (see Cornou and Lundbye-Christensen, 2008, for detailed description).

Besides, video analysis was performed for a complete 24-h time series, for one sow. This series was used to assess the performance of classification method under realistic conditions. Results from video analysis were divided into 2 min intervals; when the sow changed activity type during a 2 min interval, the activity type which was performed longest was chosen to be the one representing this interval.

1.2. Modeling of the acceleration patterns

1.2.1. Model design

Modeling and monitoring of the activity types are based on time series previously averaged per second.

The first suggested model is univariate and includes gradually changing level and sinusoid movements, as in Cornou and Lundbye-Christensen (2008). The observation at time t, Y_t, is linked linearly to a latent parameter vector, Q_t, by the following relation;

$$Y_t = F_t^T\theta_t + v_t, \quad v_t \sim N(0, V) \qquad (1)$$

Letting the regressor F be

$$F_t^T = (1, s_t, c_t) \qquad s_t = \sin\tfrac{2\pi}{T}t \qquad c_t = \cos\tfrac{2\pi}{T}t \qquad (2)$$

the latent process consists of three components, the first reflecting the level of Y_t and the two latter modeling a sinusoid movement. The value of the period T is set to 22 s, corresponding to the averaged observed sinusoid movement: analysis of auto-correlation of both Learning and *Test* data sets showed periodic movement with a period ranging from 19 to 25 s, for 50% of the feeding series. The evolution over time of Q is modeled as a random walk:

$$\theta_i = \theta_{i-1} + \omega_{i\,\iota} \qquad \omega_t \sim N(0, W) \qquad (3)$$

Initial values for the series are given by $\omega_0 \sim N(m_0, C_0)$

The error sequences v_t and ω_t are assumed to be internally and mutually independent. Hereby the signal, Y_t, consists of noisy observations of a smoothly changing trend added to a semi-periodic term with smoothly changing amplitude and phase.

The evolution variance W governs the variation over time in the level (W^μ) and the sinusoid component (W^{sc}):

$$W = W_U = \begin{pmatrix} W^\mu & 0 & 0 \\ 0 & W^{sc} & 0 \\ 0 & 0 & W^{sc} \end{pmatrix} \qquad (4)$$

The variations in trend and the sinusoid component are assumed to be independent. Moreover, the suggested variance structure ensures that the increments of the sine, cosine terms are uniformly distributed over the angles independent of the amplitude.

For known initial values and variance parameters, the updating equations of the DLM estimate the underlying state vector Q by its conditional mean vector m_t and its variance-co-variance matrix C_t (the model variance) given all previous observations $D_t = \{Y_{1r}, \ldots, Y_t\}$ of the acceleration measurements. The conditional distributions of the predictions are

$$(\theta_t | D_t) \sim N(m_t, C_t), \qquad (Y_t | D_{t-1}) \sim N(f_t, Q_t) \qquad (5)$$

The updating equations for stepwise calculation of m_t, C_t, f_t and Q_t can be found in West and Harrison (1997, pp. 103-104).

A multivariate generalization of this model involves a three-dimensional observational vector (x_t, y_t, z_t) and a nine dimensional latent process θ_t:

$$Y_t = \begin{pmatrix} x_t \\ y_t \\ z_t \end{pmatrix} = F_t^T \theta_t + \nu_t, \qquad \nu_t \sim N(0, VI) \qquad (6)$$

assuming the observational noise to be normal, independent over coordinates, with variance V, and I as the 3×3 identity matrix.

The latent process is organized with three trend coordinates, and six cyclic coordinates. The regressor matrix is

$$F_t^T = \begin{pmatrix} 1 & 0 & 0 & s_t & 0 & 0 & c_t & 0 & 0 \\ 0 & 1 & 0 & 0 & s_t & 0 & 0 & c_t & 0 \\ 0 & 0 & 1 & 0 & 0 & s_t & 0 & 0 & c_t \end{pmatrix} \qquad (7)$$

where s_t and c_t are defined as in (2). The evolution over time is modeled as in the univariate case by a random walk (3).

There are several choices of variance structure of the evolution variance W. We consider the following three choices of symmetric matrices in this paper:

$$W = W_{M1} = \begin{bmatrix} W_x^\mu & W_{xy}^\mu & W_{xz}^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & W_y^\mu & W_{yz}^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & W_z^\mu & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & . & W_x^s & W_{xy}^s & W_{xz}^s & 0 & 0 & 0 \\ . & . & . & . & W_y^s & W_{yz}^s & 0 & 0 & 0 \\ . & . & . & . & . & W_z^s & 0 & 0 & 0 \\ . & . & . & . & . & . & W_x^c & W_{xy}^c & W_{xz}^c \\ . & . & . & . & . & . & . & W_y^c & W_{yz}^c \\ . & . & . & . & . & . & . & . & W_z^c \end{bmatrix} \qquad (8)$$

$$W = W_{M2} = \begin{bmatrix} W_x^{\mu} & W_{xy}^{\mu} & W_{xz}^{\mu} & 0 & 0 & 0 & 0 & 0 & 0 \\ . & W_y^{\mu} & W_{yz}^{\mu} & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & W_z^{\mu} & 0 & 0 & 0 & 0 & 0 & 0 \\ . & . & . & W_x^{s} & W_{xy}^{s} & W_{xz}^{s} & W_{xx}^{sc} & W_{xy}^{sc} & W_{xz}^{sc} \\ . & . & . & . & W_y^{s} & W_{yz}^{s} & W_{yx}^{sc} & W_{yy}^{sc} & W_{yz}^{sc} \\ . & . & . & . & . & W_z^{s} & W_{zx}^{sc} & W_{zy}^{sc} & W_{zz}^{sc} \\ . & . & . & . & . & . & W_x^{c} & W_{xy}^{c} & W_{xz}^{c} \\ . & . & . & . & . & . & . & W_y^{c} & W_{yz}^{c} \\ . & . & . & . & . & . & . & . & W_z^{c} \end{bmatrix} \quad (9)$$

$$W = W_{M3} = \begin{bmatrix} W_x^{\mu} & W_{xy}^{\mu} & W_{xz}^{\mu} & W_{xx}^{\mu s} & W_{xy}^{\mu s} & W_{xz}^{\mu s} & W_{xx}^{\mu c} & W_{xy}^{\mu c} & W_{xz}^{\mu c} \\ . & W_y^{\mu} & W_{yz}^{\mu} & W_{yx}^{\mu s} & W_{yy}^{\mu s} & W_{yz}^{\mu s} & W_{yx}^{\mu c} & W_{yy}^{\mu c} & W_{yz}^{\mu c} \\ . & . & W_z^{\mu} & W_{zx}^{\mu s} & W_{zy}^{\mu s} & W_{zz}^{\mu s} & W_{zx}^{\mu c} & W_{zy}^{\mu c} & W_{zz}^{\mu c} \\ . & . & . & W_x^{s} & W_{xy}^{s} & W_{xz}^{s} & W_{xx}^{sc} & W_{xy}^{sc} & W_{xz}^{sc} \\ . & . & . & . & W_y^{s} & W_{yz}^{s} & W_{yx}^{sc} & W_{yy}^{sc} & W_{yz}^{sc} \\ . & . & . & . & . & W_z^{s} & W_{zx}^{sc} & W_{zy}^{sc} & W_{zz}^{sc} \\ . & . & . & . & . & . & W_x^{c} & W_{xy}^{c} & W_{xz}^{c} \\ . & . & . & . & . & . & . & W_y^{c} & W_{yz}^{c} \\ . & . & . & . & . & . & . & . & W_z^{c} \end{bmatrix} \quad (10)$$

Model (8) is similar to the univariate model (1)-(4) with correlation between the x, y and z coordinates. In model (9) we allow for a general variance structure over the coordinates in the sinusoid component, and in model (10) the variance structure is completely free allowing for correlation between the trend and the cyclic component. For models (8)-(10), dots indicate that the matrices are symmetric.

The updating equations apply for the multivariate model as in the univariate case giving recursions for the filtered distribution $(\theta_t|D_t)\sim N(m_t, C_t)$ and the predictive distribution $(Y_t|D_{t-1})\sim N(f_t, Q_t)$.

Each of the three models (M1- M3) is used to describe all five activity types. For each model, the five activities are characterized by their activity-specific parameters ***(V*** and ***W).*** Estimation of these parameters is presented Section 1.2.2.

An alternative fourth multivariate model, MU, consists in combining the three axes of the univariate model, assuming independence. This model is characterized by the axis-specific parameters of the univariate model.

1.2.2. Parameters estimation and model diagnostics

For both the univariate and the multivariate models, the observation variances V and the parameters of the system variances W, characteristic of each axis of the respective activities, are estimated using the EM algorithm (Dempster *et al.,* 1977; J0rgensen *et al.,* 1996; Dethlefsen, 2001). 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 (5), and their respective smoothed components $\tilde{m}_t$ and $\tilde{C}_t$ (West and Harrison, 1997, p. 113).

Model fit is checked by defining the following residuals:

$$r_t = Y_t - f_t \;\sim\; N(0, Q_t) \tag{11}$$

where f_t is the prediction of Y_t given the past. These residuals are standardized with respect to the forecast variance Q_t as

$$\tilde{r}_t = Q_t^{-1/2} r_t \;\sim\; N(0, I) \tag{12}$$

These residuals or the standardized residuals are analyzed coordinatewise. Provided a good model fit, these residuals are mutually independent and normally distributed. For both r_t and $\mathbf{f}_t$, auto-correlation plots, QQ-plots and time-plots may illuminate possible lack of fit.

1.2.3. Monitoring: activity classification

Automatic classification of the activity types is performed by a Multi-Process Kalman Filter (MPKF), as in Cornou and Lundbye-Christensen (2008).

Each DLM is characterized by the variance parameters M_t: α(/) = {¾/(/), W(/)} where α(/) holds for all t. In the Multi-Process model of class I, a single DLM (out of a range of possible DLMs) is appropriate for describing the entire time series. However, there is uncertainty about the 'true' value of the defining parameter vector a = a(/), where a(/) is the set of parameters for the 5 possible DLMs, i.e. the five activity types indexed by $i \in$ {FE, WA, RO, LL, LS}.

Each DLM, M_t (a), is analyzed using the updating equations. At each time t, the posterior probabilities (p_t) are calculated for each i, as

$$p_t(i) \propto \varphi_t(i) \times p_{t-1}(i), \tag{13}$$

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

The predictive distribution, based on (5), is

$$\varphi_t(i) = \frac{1}{\sqrt{det 2\pi Q_t}} \exp\left(-\frac{1}{2}(Y_t - f_t)^T Q_t^{-1}(Y_t - f_t)\right) \tag{14}$$

Each DLM is analyzed using all pairs of 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. It deserves notice that (13) and (14) hold both for the univariate and multivariate cases. In the ad hoc multivariate model MU, $\varphi_t(i)$ is calculated as the product of the predictive distribution obtained for each axis of the univariate model.

Each 2 min series of the *Test* data set is analyzed as follow: (1) For each observation (s), the activity type result (observation result) is determined as being the one with the highest posterior probability. (2) Then, for each series, the activity type which has the largest number of observation results is determined as series result. Because of learning characteristic of the DLM, series results are computed only for the last 60 s of each 2 min series.

1.2.4. Monitoring: evaluation

When a particular activity type is performed, this can be either recognized as such (TP: true positive) or not recognized (FN: false negative). When this same activity is not performed, this can be recognized as such, i.e. not performed (TN: true negative) or recognized as being performed (FP: false positive).

The outcome of the monitoring algorithm can be defined in terms of sensitivity (sens) and specificity (spec), for each activity type (Feinstein, 1975). Sensitivity is the probability of detecting the correct activity, when this activity is being performed and is calculated as sens = TP/(TP + FN). Specificity is the likelihood that an activity is not detected, when not performed, and is calculated as spec = TN/(TN + FP).

Predictive values pred are calculated from sens and spec corrected for the distribution of time spent performing each activity type (prev) as

$$pred = \frac{sens \times prev}{sens \times prev + (1 - spec) \times (1 - prev)}$$

1.3. Results

Each activity type is modeled, and thereafter monitored, using its activity-specific variance parameters. A first set of parameters, estimated from the *Learning* data set is presented in Section 1.3.1. Section 1.3.2 presents results of the classification method applied on the *Test* data set.

As a control for consistency, a second set of parameters is estimated from the *Test* data set, and the classification method is applied on the *Learning* data set, using this second set of parameters.

1.3.1. Estimates

Using the *Learning* data set, the variance parameters are estimated using the EM algorithm (1000 iterations). For the four models, we obtained a set of values of the variance parameters (V and W) for each of the five activity types. Estimation of a second set of parameters, using from the *Test* data set (EM algorithm, 1000 iterations) shows consistent results: parameters values estimated from both data sets appear very similar. The entire set of values is available on request.

An example of estimated results (for model M3) is shown in Fig. 1. It can be seen that the five activity types are best differentiated by their respective observation variance *V* (left plot): in other words, most of the variation observed within the activity types is described by the model in the observation variance. It deserves notice that the observation variance, beside describing measurement errors, also includes short term variations of the series. This may explain the different values of V in between the activity types. For the evolution variance W, the values of the estimated parameters of the level components (W_μ^χ, W_μ^ν and W_μ^ζ) tend to be smaller. Only RO and WA have high values for the first element of the variance matrix, which correspond to the axis measuring horizontal forward acceleration. This is in accordance with the movement of the sows performing these activities. The values of the sinusoid components of the evolution variance (not plotted here) tend to be even smaller: these values range from 10^{-4} (FE) to 10^{-8} (LL); as for the observation variance, the estimated values for the activity types decrease according to the level of variation within the activity.

Model control by mean of auto-correlation plots reveals the presence of a sinusoid pattern (of period T ¾ 22) in most of the residuals of the series with no periodic movement (RO, WA, LS and LL). This indicates that the sinusoid pattern of period T is 'forced' on these series, and should be excluded.

An additional parameter estimation, without the sinusoid components) is therefore performed for all four models and for each activity type. The new estimated parameters converge after 500 iterations of the EM algorithm.

The new estimated values for V and W_μ are very similar to the previous ones, for the four activity types with no periodic movement (RO, WA, LS and LL). This is in accordance with the results of the first parameter estimation, which shown very small values for their sinusoid component(s) (from 10^{-5} to 10^{-8}).

An additional model control for these activities, where the sinusoid component(s) is excluded, reveals a better fit: the residuals of these activities show no longer a periodic movement.

It can also be noticed that modeling FE activity with no sinusoid component results in an increase of the estimated values for W_μ for the univariate (x 18, 9.5 and 21 for x, y and z) and multivariate (x7, 3 and

17 *for x, y* and z) models. This indicates that the variation previously described in the sinusoid component(s) of the evolution variance is in that case transferred to the level component. The absence of sinusoid component also affects, to a smaller degree, the estimated values for the observation variance *V:* x 0.74, 0.6 and 0.74 for the axes x, *y* and *z* of the univariate model, and x 0.74 for the multivariate model.

According to the above results, it is therefore chosen to include the sinusoid component(s) of the models only for FE, and exclude it (them) when modeling the other activity types.

1.3.2. Monitoring

Given a series of observations, posterior probabilities for the five activity types are estimated for the univariate and the four multivariate models, using the MPKF.

Results are first calculated for the *Test* data set, using the parameters estimated from the *Learning* data set. Then, parameters estimated for the *Test* data set are applied on the *Learning* data set, previously divided into series of 120 observations.

Fig. 2 illustrates the evolution of the posterior probabilities for a series of observations of LS activity, from the *Test* data set. On the top of the figure, the vector length of acceleration ($\sqrt{x^2+y^2+z^2}$) of the given series is plotted. The classification method first indicates that the sow is lying laterally, then walking and after approximately 30 s, lying sternally. The slight increase in activity (due to a sudden movement of the sow), which is seen on the top plot at about 18 s, resulted here in an increase of posterior probabilities for the walking activity at that time.

An observation is correctly classified when the output result from the MPKF (Section 1.2.3) corresponds to the activity type of the given series. The percentage of observations correctly classified, using the multivariate models Ml, M2 and M3 only differ of 1% for FE, 2% for RO and is identical for WA, LS, and LL. As the suggested models are predictive models, cross-validation may be amore suitable way of selecting the best performing model. We have chosen M3 as the overall best performing model, therefore only results obtained using from M3 are reported.

Table 1: Percentage of observations correctly classified by the MPKF after 60 s, using parameters estimated for the univariate model, multivariate MU and multivariate M3. Left panel: 5040, 4740, 6420, 6600 and 6600 observations for FE, RO, WA, LS and LL; right panel: 1800, 2100, 3300, 3300 and 3300 for FE, RO, WA, LS and LL.

	Test data set Univariate			Multivariate		Learning Univariate			Multivariate	
	x	*y*	z	MU	M3	*x*	*Y*	z	MU	M3
FE	39	75	44	75	79	44	49	58	61	86
RO	74	17	38	67	56	51	20	33	64	57
WA	82	27	14	72	74	71	33	20	54	58
LS	23	25	13	24	30	7	63	72	68	19
LL	85	84	84	82	83	96	2	1	2	75
Pattern collapsing										
Active	98	73	73	96	96	100	82	86	97	97
Passive	92	92	90	90	94	90	90	90	89	91

Table 1 shows the percentage of the last 60 s of the series correctly classified by the MPKF. Results are presented for both the three axes of the univariate model and the multivariate models MU and M3. Results from the *Test* data set are presented on the left panel and results from the *Learning* data set on the right panel.

For the *Test* data set, results from both multivariate models appear better than the average results of the individual axes of the univariate model, at the exception of LL. For the *Learning* data set, the percentage of recognition for LL is very poor for the multivariate model MU. This model, which combines the probabilities of the individual axes of the univariate model, seems very sensitive to the results obtained for each axis. The poor recognition by *y* and z axes may be explained by a larger variability of the *Test* data set (larger number of series), which is confirmed by larger values for LL parameters for this data set. LL was recognized as LS in 98% and 95% of the cases for the axes *y* and z, and in 95% of the cases for the model MU.

It should also be noticed that the percentages of observations correctly classified increase in most cases when the observation results are based on the last 60 observations rather than on the whole series (120 observations). For the *Test* data set, for model M3, the percentages of observations correctly classified increase with 8%, 6%, 13%, 5% and 1%, for FE, RO, WA, LS and LL. For both MU and M3, the highest increase is noticed for WA. This may indicate that the MPKF takes longer time to recognize walking activity.

The percentage of series correctly classified (series results) is very similar to the observation results: differences range from 0% to 3%.

Pattern collapsing is performed by grouping activity types into two categories. FE, RO and WA are grouped into the 'active' category; LS and LL into the 'passive' category. Observations are correctly classified when an activity type is recognized as being in its own category. As seen in the bottom of Table 1, the multivariate model M3 performed best: 96% and 94% of, respectively active and passive categories are correctly classified. For the *Learning* data set, results are 97% and 91%.

Fig. 3 shows the distribution of the results of the MPKF for each activity type using parameters from model M3.

For both *Test* (a) and *Learning* (b) data sets, RO activity is recognized as WA for, respectively, 38% and 30% of the observations. An explanation is the fact that RO and WA activities are often per formed concomitantly. Regarding LS, the MPKF recognized it as LL for, respectively, 61% and 64% of the observations. This rather low percentage of recognition of LS may be due to the choice of the extracted time series in this experiment, where the LS position of the sow was often very close to a LL position.

The classification method is also implemented on a *Previous* data set used in Cornou and Lundbye-Christensen (2008). After parameters estimation following the procedure described in Section 1.2.2, the MPKF is implemented for the five respective models. Results of the MPKF implemented using model M3 are shown in Fig. 3(c). The percentages of observation correctly classified are 100%, 100%, 92%, 93% and 75% for, respectively, FE, RO, WA, LS and LL. These percentages reach 100% and 96% when the activity types are collapsed into the respective active and passive categories.

The differences of results observed between the data sets used in this Example and the Previous data set from Cornou and Lundbye-Christensen (2008) may be explained by the number of observations. The data set of Cornou and Lundbye-Christensen (2008) consists of 50 series and the *Test* and *Learning* data sets consist of 490 and 230 series, respectively. A larger number of series, extracted from a larger number of individuals (11 sows vs. 5 sows), may have increased the variability.

A 24 h times series corresponding to the activity of one sow is previously divided into 2min intervals and analyzed according to Section 1.2.3.

Table 2: Results, in percentages, for sensitivity (sens), specificity (spec), positive predictive values (pred +) for the activity types and categories, for multivariate model M3, for Test and Learning data set. Prevalence for the activities are indicated in the left column.

	Prevalence	Test data set			Learning data set		
		sens	spec	pred +	sens	spec	pred
FE	0.6	79	96	10	86	94	8
RO	2.2	56	95	22	57	90	12
WA	16.1	74	86	50	58	89	50
LS	22.8	30	94	59	19	92	41
LL	58.3	83	85	88	75	84	87
Active	18.9	96	94	79	97	91	73
Passive	81.1	94	96	99	91	97	99

Fig. 4 illustrates the results obtained, for the first 6 h (00:00-06:00 am). In this example, the MPKF is applied using estimated parameters from the multivariate model M3. Fig. 4(a) shows the values of the vector length of acceleration. Two periods of high activity are observed, at about 02 and 05 am. As shown in Fig. 4(b), the categories of activity, both observed by video analysis and automatically classified by the MPKF show very similar results, for the given 6 h period. For the entire day, the percentage of series correctly classified is 100%, 56%, 53%, 23% and 74% for FE, RO, WA, LS and LL activity, and 82% and 93% for the active and passive categories.

Results for the model M3, applied on the *Test* and *Learning* data sets are summarized in Table 2. Predictive values are estimated using the prevalence of activity types and categories in this 24 h period.

The specificity of the method for classifying activity types, ranges from 84% to 96% for the data sets used in this Example. Positive predictive values, which is the probability for a sow to perform the activity indicated by the classification method, are very dependent of the prevalence of each activity type. Due to small prevalences, the predictive values of active categories are quite low, despite relative high sensitivity and specificity. FE activity, which is rarely observed has therefore a very low positive predictive value. By collapsing into active and passive categories, this is improved : 79% and 73% for the active category (for *Test* and *Learning)* and 99% for the passive category (for *Test* and *Learning).*

1.4. Discussion and conclusion

Results tend to indicate that multivariate models are better suited than the univariate and ad hoc multivariate (MU) models for monitoring activity types for group-housed sows. The percentage of activities and categories correctly classified by the multivariate models tend to be higher than the averaged axes results of the univariate model. The structure of the evolution variance of the multivariate models does not seem to influence their performances. This may be explained by the fact that the activity-specific variance lies mainly within the models' short term variation, described by the observation variance.

As seen especially for the *Learning* data set, the multivariate models M1-M3 perform better than the ad hoc multivariate model MU, which combines the posterior probabilities of the univariate model's three axes. Moreover, the use of multivariate models of type M1-M3 seems more appropriate. With regards to mathematical modeling, both univariate model and MU treat the 'dependent' three-dimensional axes as independent variables. In that case, a high or low performance of MU may reflect the performance of one particular axis of the univariate model. As reported here and in Cornou and Lundbye-Christensen (2008), some particular axes are best suited to recognize a given activity.

Besides, practical application of this monitoring method for group-housed sows may imply that the accelerometer is placed on an ear-chip. In that case the best suited model will probably be a coordinate-free multivariate model, where the position of the axes is updated over time. This type of model is not trivial and calls for further research.

In order to assess potential improvements in the modeling and monitoring part, the methods described in this Example were applied on a *Previous* data set used in Cornou and Lundbye-Christensen (2008). Results indicate that the performance of the same univariate model is improved. Previous results were based on the percentage of posterior probability exceeding p = 0.5, for an entire series, i.e. 120 observations. In this Example, the observation results are based on the maximum posterior probability of a given activity type, and computed for the last 60 observations. This computational method seems more correct and may have helped improving the results. It should also be noticed that parameter estimation, for a given activity, is here based on the entire series of the data sets; in the previous paper, model's parameters were estimated for each series, and parameters were computed as the averaged result of each 10 min series. This may also be a factor of improvement.

Collapsing of the activity types into 'active' and 'passive' categories was performed. Multivariate models M1-M3 show the best results for both (/) *Test* and (ii) *Learning* data sets of this Example, as well as for the (iii) Previous data set from Cornou and Lundbye-Christensen (2008) : 96%, 97% and 100% for the active category and 94%, 91% and 96% for the passive category (for (/), (ii) and (iii), respectively). These results are better than the ones reported, for instance, by Umstatter *et al.* (2008), where, for sheep, both categories were correctly classified in 90% of the cases, or by Nadimi *et al.* (2007) who reported a success rate of 80% when categorizing cows' activity into active and passive.

It can be questioned how necessary it is to distinguish between, for instance, LS and LL, or WA, RO and FE activity types, if the final purpose is to classify activities as 'active' vs. 'passive'. A model that directly distinguishes between 'active' and 'passive' was not attempted in this Example. Nevertheless, at the view of the existing variation of the series between the activity types, such a two step classification seems more realistic.

Potential applications of the modeling and monitoring method described in this Example are numerous: welfare, social behavior, health monitoring, from the mating section to the farrowing house.

For group-housed sows, an example of direct application is to develop a method that automatically detect the onset of oestrus, by monitoring the activity level of individual sows. The results obtained here, in terms of category classification seems satisfying for this purpose. Another potential application is monitoring the approach of farrowing : the activity level of sows is expected to increase during the last 24 h before farrowing (Oliviero *et al.*, 2008; Erez and Hartsock, 1990).

In conclusion, the results presented in this Example indicate that multivariate models are well suited to categorize activity types, and particularly activity categories, for group-housed sows. Potential improvements of the model include the development of an axis-free multivariate model.

Example 2

Development of automation systems for pig production has, so far, mainly focused on reproduction management - with emphasis on oestrus detection (Serlet, 2004; 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 J0rgensen, 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 an radiotelemetric device implanted under the skin close to 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) suggested monitoring methods to classify activity types for sows housed in a large pen; 3-dimensional accelerometers have also been used for monitoring cows' behavior patterns (Martiskainen *et al.,* 2009).

The objective of this Example is to develop a specific method according to the invention 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 record activity patterns to assess behavioural deviations around the onset of farrowing, for sows with and without provision of bedding material.

2.1 Material and Methods

2.1.1 Animals, housing and measurements

A total of 24 sows 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 60cm wide and 195cm long (155cm x 225cm external). 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). 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 as in Example 1. Artificial light was on during the night, in order to provide sufficient lightning for video recording.

2.1.2 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 and the exact onset of farrowing for each experimental sow.

2.2. Modeling 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) LI : 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 DLM. Estimation of the activity specific variance parameters is performed using a *Learning* data set including 8 series (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* data set, which consists of 24 series (2 x 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).

2.2.1 Modeling: Specifications of the multivariate DLMs

The multivariate DLM involves the three-dimensional observational vector (x_t, y_t, z_t) and a three-dimensional latent process Q_t. The observation equation (6) of Example 1 describes the sampling distribution of the observation vector Y_t assuming the observational noise to be normal, independent over coordinates, and with variance V and identity matrix I. The evolution over time of t is modeled according to equation (3) of Example 1.

The observation variance V, is a diagonal 3x3 matrix with a same parameter value for axes x, y and z. The evolution variance W is a 3x3 matrix with a completely free structure, allowing for correlation between the axes; this corresponds to the multivariate model M3 described in Example 1.

The DLM estimates the underlying state vector Q_t by its conditional mean vector m_t and its variance-co-variance matrix C_t as done in Example 1.

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;

J0rgensen *et al.,* 1996; Dethlefsen, 2001).

Results of the estimated parameters converge after 800 iterations and are presented in Table 3. The estimated parameters indicate that the more active is a type of behaviour, the larger are the associated variances. Most of the variance appears to be located in the diagonal components of the system variance *W.*

Table 3 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 (LI), 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.

	HA	MA	L1	L2	LS
V	$2.5e^{-2}$	$6.4e^{-2}$	$1.3e^{-2}$	$1.1e^{-2}$	$6.6e^{-3}$
W_x	1.1	$2.5e^{-1}$	$5.2e^{-4}$	$1.2e^{-4}$	$1.7e^{-3}$
Wy	2.2	$3.6e^{-1}$	$2.6e^{-3}$	$3.6e^{-3}$	$8.4e^{-5}$
W_z	$9.6e^{-1}$	$6.7e^{-2}$	$4.3e^{-3}$	$2.6e^{-3}$	$2.8e^{-4}$

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.

2.2.2 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) and Example 1.

Each DLM is characterized by the variance parameters M_t: $\alpha(l)$ = $\{V(l), W(l)\}$ where $\alpha(l)$ holds for all t; there is uncertainty about the 'true' value of the defining parameter vector a = a(/), where a(/) is the set of parameters for the 5 possible DLMs, i.e. the five activity types indexed by iϵ {HA, MA, LI, L2, LS}. Each DLM, M_t (a), is analyzed using the updating equations. At each time t, the posterior probabilities (p_t) are calculated for each / using equation (14) of Example 1.

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) and in Example 1.

2.2.3 Validation of the classification method

Each 2 minutes series of the *Test* data set is analyzed using the parameters of the *Learning* data set. Moreover, the parameters previously estimated using the *Test* data set, are used to analyze the *Learning* data set, previously divided into series of two minutes.

Output results are computed as follow: i) for each observation, 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 LI, $\bar{x}$ < 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 (LI, L2 and LS).

Results for both data sets are presented in Table 4. The percentage of series correctly classified by the MPKF is seen in diagonal. For both data sets, the activity types LI, 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 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.

Table 4 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 (LI), Lying side 2 (L2), Lying sternally (LS). In rows: percentage of series results, for the five activity types, as classified by the MPKF.

	MPKF on *Test* set					MPKF on *Learning* set				
	HA	MA	LI	L2	LS	HA	MA	LI	L2	LS
HA	90.6	9.4	0	0	0	92.5	7.5	0	0	0
MA	20.8	75.0	0	0	4.2	12.5	80	0	0	7.5
LI	0	2.1	97.9	0	0	0	0	100	0	0
L2	0	3.1	0	96.9	0	0	0	0	100	0
LS	0	5.2	0	0	94.8	0	0	0	0	100

When grouping the activity types into active (HA and MA) vs. passive (LI, 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. Finally, it can be noticed that none of the passive series is misclassified as HA, as no HA series is misclassified as passive.

2.3. 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 2.2.3. Additionally, i) results from series where the number of missing observation 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 LI, L2 or LS using the suggested thresholds is in some cases not possible (due 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 (LI, L2, LS or LU), is re-classified as the previous passive behaviour type, and reciprocally.

Figure 5 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. 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 (LI or L2).

Figure 6 shows the series and corresponding output results for the same sow as Figure 5, 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, the entire experimental period is divided in 24 hours intervals around farrowing. These intervals are computed backward and forward, for each sow, around the onset of farrowing (hO).

Figure 7 illustrates, for each 24 hours interval, the percentage of time spent per forming the different activities, for sows receiving bedding material (a) and sows receiving no bedding material (b); dO represents the last 24 hour period before the onset of farrowing (i.e. h-24 to hO). 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.

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%(±14.7) (group S) and 53.3%(±17.5) (group NS), as compared to a daily average of 30.1%(±7.7) (group S) and 25.1%(±9.8) (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 (LI and L2) decreases on dO. The percentage of misclassified Lying and passive (LU) activity is rather small: 4.7% in average, for the 19 sows for the entire experimental period. The total number of 2 min series classified as LU ranges from 9 to

676 for the 19 sows (average of 205 ± 160). Series from three sows (for which the LU 2 min periods totals at 363, 414 and 676) represent 63.3% of these series. This may be explained by the fact that these specific sows had more loosen neck collars that the others.

The left side of Figure 8 shows the number of changes of activity types sows per form, for each 24 hours period, for sows from group S (al), and group NS (bl). A change of activity is computed each time a sow's activity type, as classified by the MPKF, changes from one to another. For both groups, the number of changes of activity type is strongly increasing from d-1 to dO, both for HA (x 2.7 and x 2.6, for group S and NS, respectively) and MA (x l.9 and x2.0, for group S and NS, respectively). The averaged number of changes for lying laterally (mean value for LI and L2) stays relatively constant over the entire period, for both groups.

The right side of Figure 8 shows the length, or number of 2 min series (daily averaged) 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 dO (x0.42 and x0.40, 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 7, on top of the bar plots).

Figure 9 illustrates the percentage of time spent per hour, performing HA, MA and lying laterally (sum of LI and L2) activities. Results are shown from 48 hours before the onset of farrowing (hO) 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 hO, 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.

2.4. Discussion and Conclusion

The method suggested in this Example 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, LI, L2, LS). When collapsing activity types into active (HA and MA) vs. passive (LI, L2, LS) categories, results range from 96 to 100%.

What is here qualified 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 (LI), 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 (LI, L2 and LS). Before correction 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 resuit 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 (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 Example are straightforward. Detecting the onset of farrowing by monitoring behavioral 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 behavioral changes occurs 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 behavioral 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 of farrowing housing systems. Besides, 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 Example 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 Example 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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P A T E N T C L A I M S

1. A method for preparing a model for classifying an activity type of a farm animal, the method comprising the steps of:

providing a farm animal with an acceleration sensor; recording data for acceleration over time in dimensions x, y and z from the acceleration sensor; observing the farm animal; synchronising with respect to time the observation of the farm animal with the data from the acceleration sensor; defining an activity type for the farm animal; classifying the activity of the farm animal from the observation of the farm animal according to the defined activity type during a period of time; applying the data from the acceleration sensor obtained during the period of time to prepare the model, which comprises

- an observation equation

$$Y_t = \begin{pmatrix} x_t \\ y_t \\ z_t \end{pmatrix} = F_t^T e_t + v_t, \qquad v_t \sim N(0, V)$$

correlating at time t an observational vector $y_t = \begin{pmatrix} x_t \\ y_t \\ z_t \end{pmatrix}$ of data for dimensions x, y and z with a regressor matrix F_t^T, a latent process vector Q_t and an observational variance V;

- a system equation

$0_t = 0_{t-1} + \omega_t, \qquad \omega_t \sim N(0, W)$

defining the evolution of the latent process vector Q_t at time t from the latent process vector 0_{t-i} at time $t-1$ and an evolution variance W at time t;

- wherein the evolution variance W indicates how the underlying mean of the latent process vector varies over time.

2. A method according to claim 1, wherein

$$\theta_t = \begin{pmatrix} \mu_t^x \\ \mu_t^y \\ \mu_t^z \\ s_t^x \\ s_t^y \\ s_t^z \\ c_t^x \\ c_t^y \\ c_t^z \end{pmatrix}$$

with $\mu_t^x, \mu_t^y, \mu_t^z$ representing trend coordinates, $s_t^x, s_t^y, s_t^z, c_t^x, c_t^y, c_t^z$ representing cyclic coordinates;

$$F_t^T = \begin{pmatrix} 1 & 0 & 0 & s_t & 0 & 0 & c_t & 0 & 0 \\ 0 & 1 & 0 & 0 & s_t & 0 & 0 & c_t & 0 \\ 0 & 0 & 1 & 0 & 0 & s_t & 0 & 0 & c_t \end{pmatrix};$$

s_t = $\mathbf{sin}\frac{2\pi}{T}t$ and $\mathbf{c}_t$ = $\mathbf{cos}\frac{2\pi}{T}t$ with the period T allowing the model to adapt to periodic movements; and

$$W = \begin{bmatrix} W_x^\mu & W_{xy}^\mu & W_{xz}^\mu & W_{xx}^{\mu s} & W_{xy}^{\mu s} & W_{xz}^{\mu s} & W_{xx}^{\mu c} & W_{xy}^{\mu c} & W_{xz}^{\mu c} \\ . & W_y^\mu & W_{yz}^\mu & W_{yx}^{\mu s} & W_{yy}^{\mu s} & W_{yz}^{\mu s} & W_{yx}^{\mu c} & W_{yy}^{\mu c} & W_{yz}^{\mu c} \\ . & . & W_z^\mu & W_{zx}^{\mu s} & W_{zy}^{\mu s} & W_{zz}^{\mu s} & W_{zx}^{\mu c} & W_{zy}^{\mu c} & W_{zz}^{\mu c} \\ . & . & . & W_x^s & W_{xy}^s & W_{xz}^s & W_{xx}^{sc} & W_{xy}^{sc} & W_{xz}^{sc} \\ . & . & . & . & W_y^s & W_{yz}^s & W_{yx}^{sc} & W_{yy}^{sc} & W_{yz}^{sc} \\ . & . & . & . & . & W_z^s & W_{zx}^{sc} & W_{zy}^{sc} & W_{zz}^{sc} \\ . & . & . & . & . & . & W_x^c & W_{xy}^c & W_{xz}^c \\ . & . & . & . & . & . & . & W_y^c & W_{yz}^c \\ . & . & . & . & . & . & . & . & W_z^c \end{bmatrix}$$

with the dots indicating that the matrix is symmetrical, and with the components $W_{subscript}^{superscript}$ of the evolution variance matrix W describing the variance between the axes indicated with the subscript and between the components of the latent process vector Q_t as indicated with the superscript.

3. A method of classifying the activity of a farm animal according to a defined activity type, the method comprising :

providing a farm animal with an acceleration sensor; recording data for acceleration over time in dimensions x, y and z from the acceleration sensor; applying the data from the acceleration sensor in a model prepared according to claim 1 or 2.

4. A method according to any one of claims 1 to 3, wherein the observational variance V and the components $W_{subscript}^{superscript}$ of the evolution variance matrix W are estimated using an expectation-maximisation algorithm.

5. A method according to any one of claims 1 to 4, wherein the data from the acceleration sensor are analysed using a multi-process Kalman Filter.

6. A method according to any one of claims 1 to 5, wherein the acceleration sensor is a digital accelerometer

7. A method according to any one of claims 1 to 6, wherein the activity type is defined as active or passive.

8. A method according to claim 7, wherein the active activity types comprise one or more of walking, running, rooting, feeding, eating, swimming, and climbing and the passive activity types comprise one or more of lying, lying laterally, lying sternally, sitting, sleeping, standing, resting, and perching.

9. A method according to any one of claims 1 to 7, wherein the activity type is defined as feeding (FE), rooting (RO), walking (WA), lying sternally (LS) or lying laterally (LL).

10. A method according to any one of claims 1 to 9, wherein the farm animal is selected from pigs, cows, sheep, goats, horses, deer, camels, elephants, hens, chickens, ducks, geese, turkeys.

11. A method according to any one of claims 1 to 10, wherein the farm animal is a pig.

12. A method according to claim 11, wherein the pig is a sow

13. A method for recording an activity pattern of a farm animal comprising classifying the activity of the farm animal according to the method of any one of claims 3 to 11 over a period of time and recording the activity of the farm animal during the period of time.

14. A method for recording an activity pattern of a farm animal according to claim 13, wherein the activity pattern relates to the reproductive or mating cycle of the farm animal.

15. A method for recording an activity pattern of a farm animal according to any one of claims 13 or 14, wherein the activity pattern comprises the relative amount of time spent by a farm animal performing a given activity or activities compared to other activities.

16. A method for recording an activity pattern of a farm animal according to any one of claims 13 to 15, wherein the number of changes in activity types over the period of time in the pattern is recorded.

17. A method for recording an activity pattern of a farm animal according to any one of claims 13 to 16, wherein the activity pattern is monitored automatically.

18. A method for recording an activity pattern of a farm animal

according to claim 17, wherein a change in the activity pattern provides a detectable signal.

19. A method for determining the physiological state of a farm animal comprising recording an activity pattern of a farm animal according to any one of claims 13 to 17 and comparing the activity pattern to a normal or otherwise predetermined activity pattern for the type of farm animal.

20. A method for determining the physiological state of a farm animal according to claim 19, wherein the physiological state is onset of oestrus, onset of farrowing, or prediction of a health disorder.

21. A system for automatically classifying the activity type of a farm animal, which system comprises

- one or more acceleration sensor boxes each comprising an acceleration sensor, a battery package and appropriate means for wirelessly transmitting data;

- means for wirelessly collecting data from the one or more acceleration sensors;

- a computer readable storage medium containing a model for classifying an activity type of a farm animal according to any one of claims 1 to 12, and computer program code configured to automatically classify the activity type of a farm animal; and

- a data processor for executing the computer program code.

22. A system for automatically classifying the activity type of a farm animal according to claim 21, wherein the computer program code is further configured to record an activity pattern of a farm animal according to any one of claims 13 to 18.

23. A system for automatically classifying the activity type of a farm animal according to any one of claims 21 or 22, wherein computer program code is further configured to determine the physiological state of a farm animal according to any one of claims 19 or 20.

24. A system for automatically classifying the activity type of a farm animal according to any one of claims 21 to 23, wherein the acceleration sensor box comprises one or more further functionalities selected from a GPS-sensor, means to fit it to a neck collar or ear tag, and a data

storage medium.

25. A system for automatically classifying the activity type of a farm animal according to any one of claims 21 to 24, wherein the system further comprises a user interface for presenting the classification of the activity type or the activity pattern of a farm animal.

26. A system for automatically classifying the activity type of a farm animal according to any one of claims 21 to 25, wherein the system further comprises a device to provide a detectable signal in case of the occurrence of a particular activity pattern.

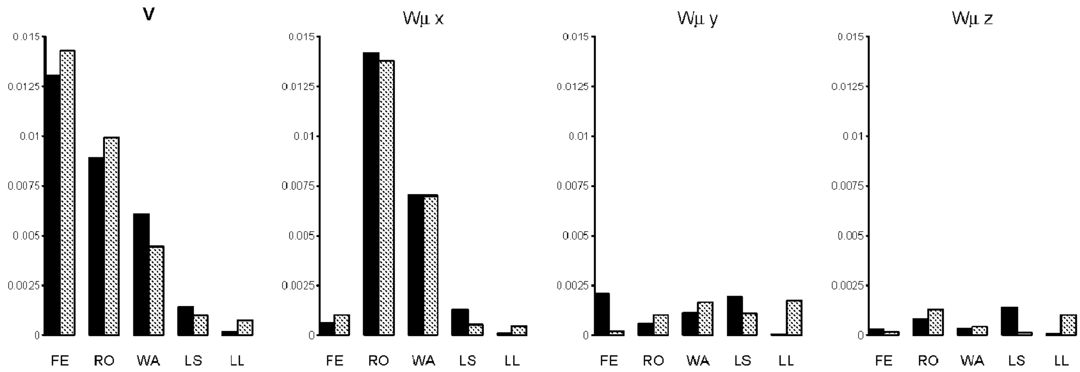
V
Wμ x
Wμ y
Wμ z
0.015
0.0125
0.01
0.0075
0.005
0.0025
0
FE RO WA LS LL

Fig. 1

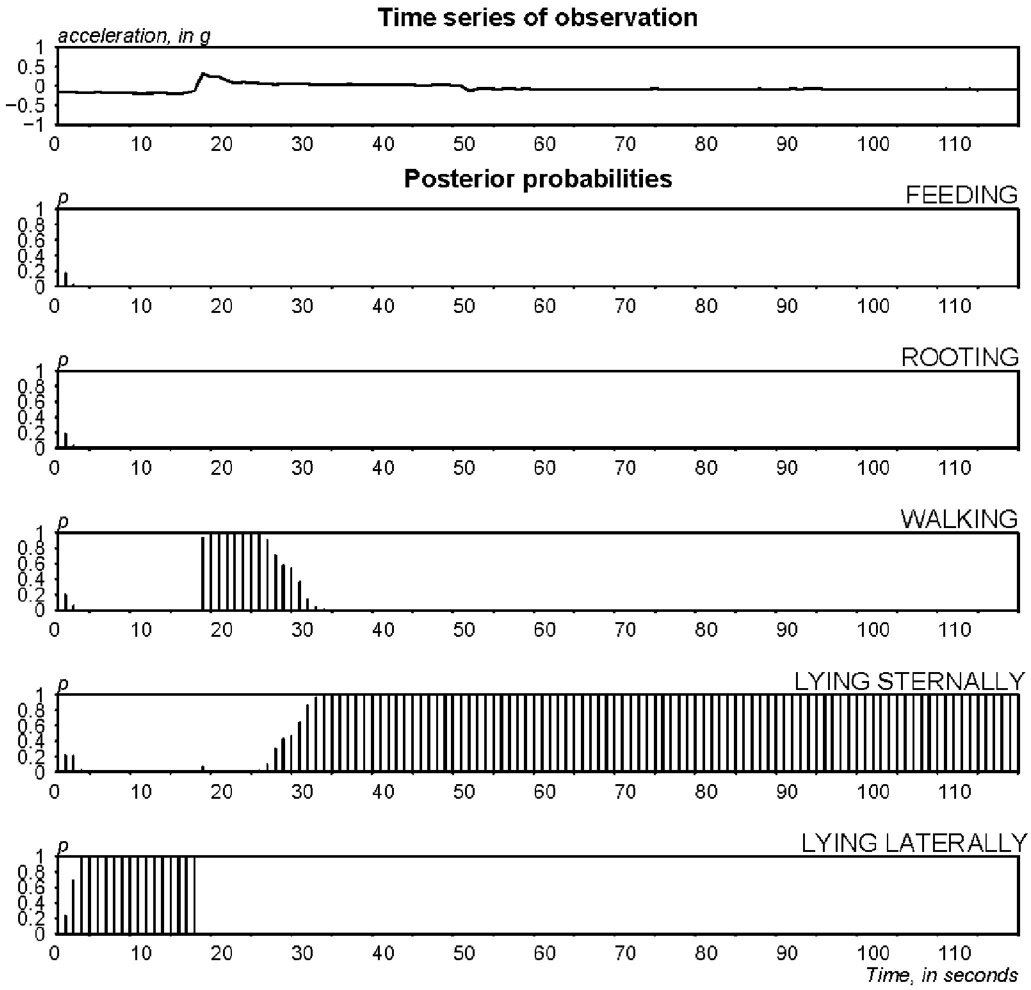
Time series of observation
acceleration, in g
Posterior probabilities
FEEDING
ROOTING
WALKING
LYING STERNALLY
LYING LATERALLY
p
Time, in seconds

Fig. 2

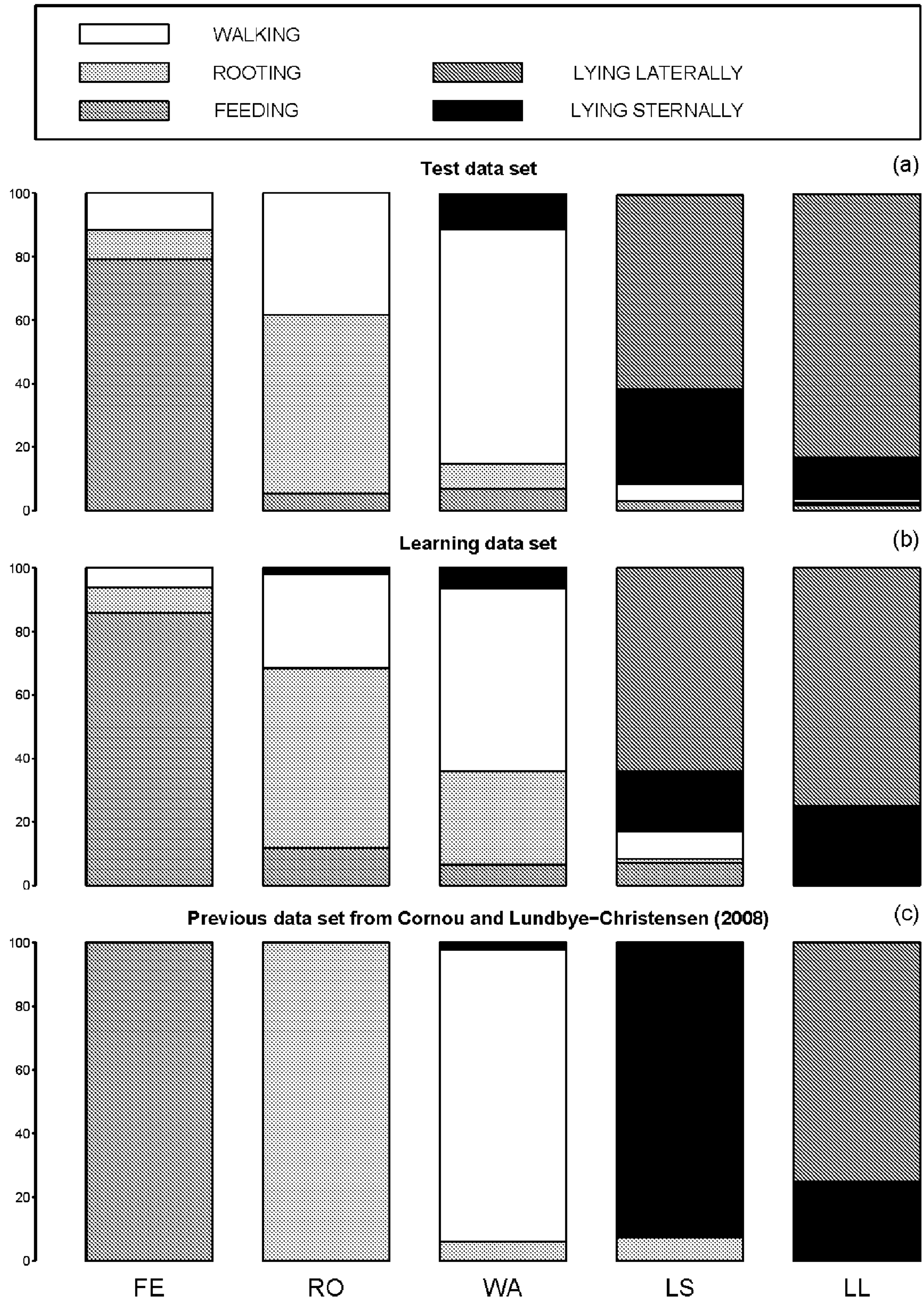
WALKING
ROOTING
FEEDING
LYING LATERALLY
LYING STERNALLY
Test data set
(a)
Learning data set
(b)
Previous data set from Cornou and Lundbye-Christensen (2008)
(c)
100
80
60
40
20
0
FE
RO
WA
LS
LL

Fig. 3

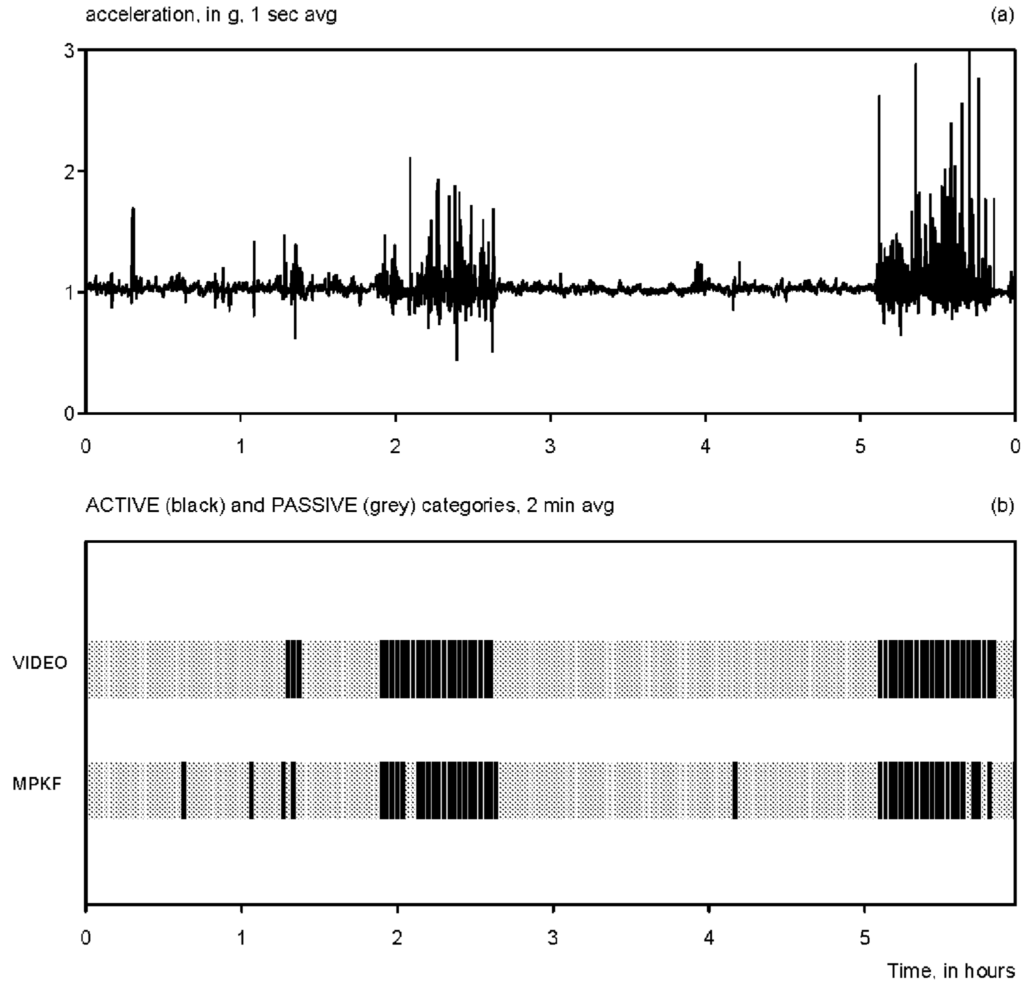
acceleration, in g, 1 sec avg
(a)
3
2
1
0
0
1
2
3
4
5
0
ACTIVE (black) and PASSIVE (grey) categories, 2 min avg
(b)
VIDEO
MPKF
0
1
2
3
4
5
Time, in hours

Fig. 4

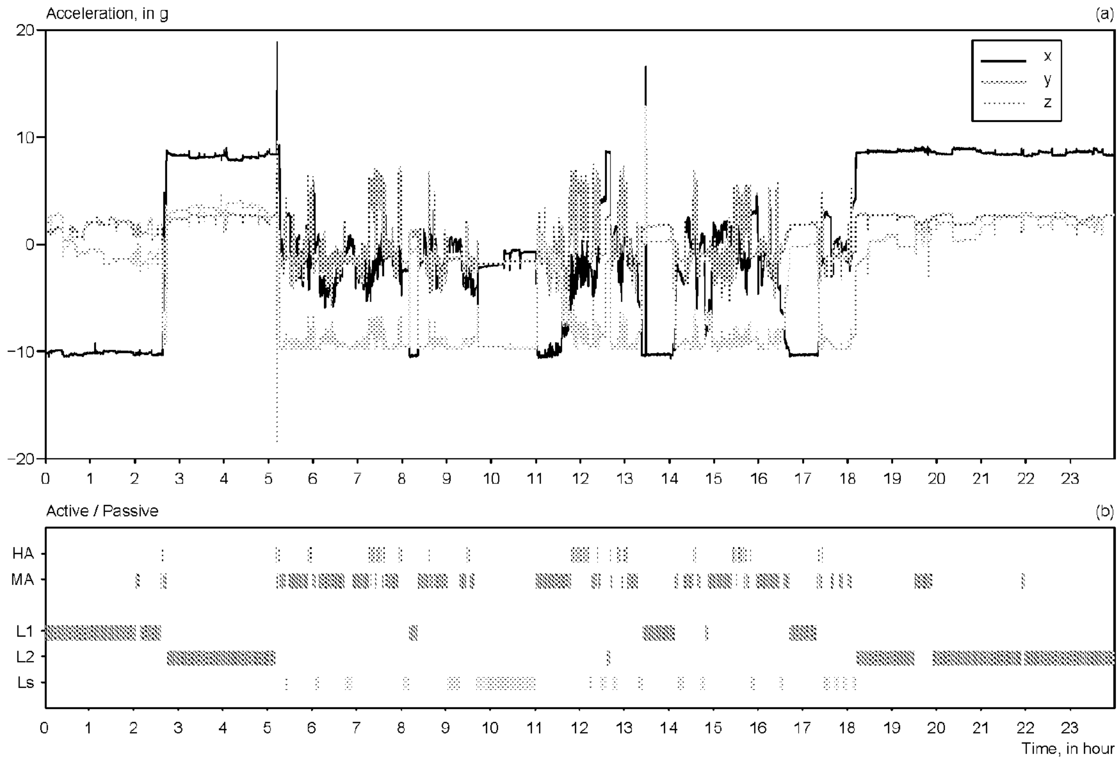
Acceleration, in g
(a)
x
y
z
20
10
0
−10
−20
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
Active / Passive
(b)
HA
MA
L1
L2
Ls
Time, in hour

Fig. 5

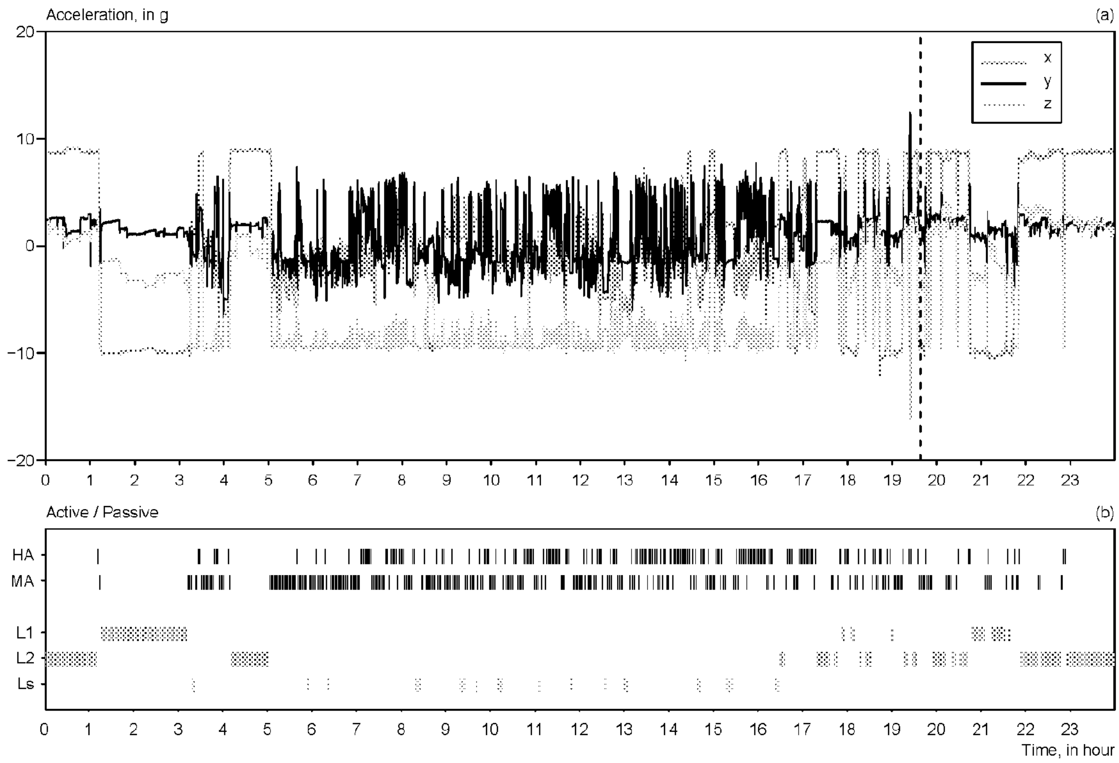
Acceleration, in g
(a)
x
y
z
20
10
0
−10
−20
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
Active / Passive
(b)
HA
MA
L1
L2
Ls
Time, in hour

Fig. 6

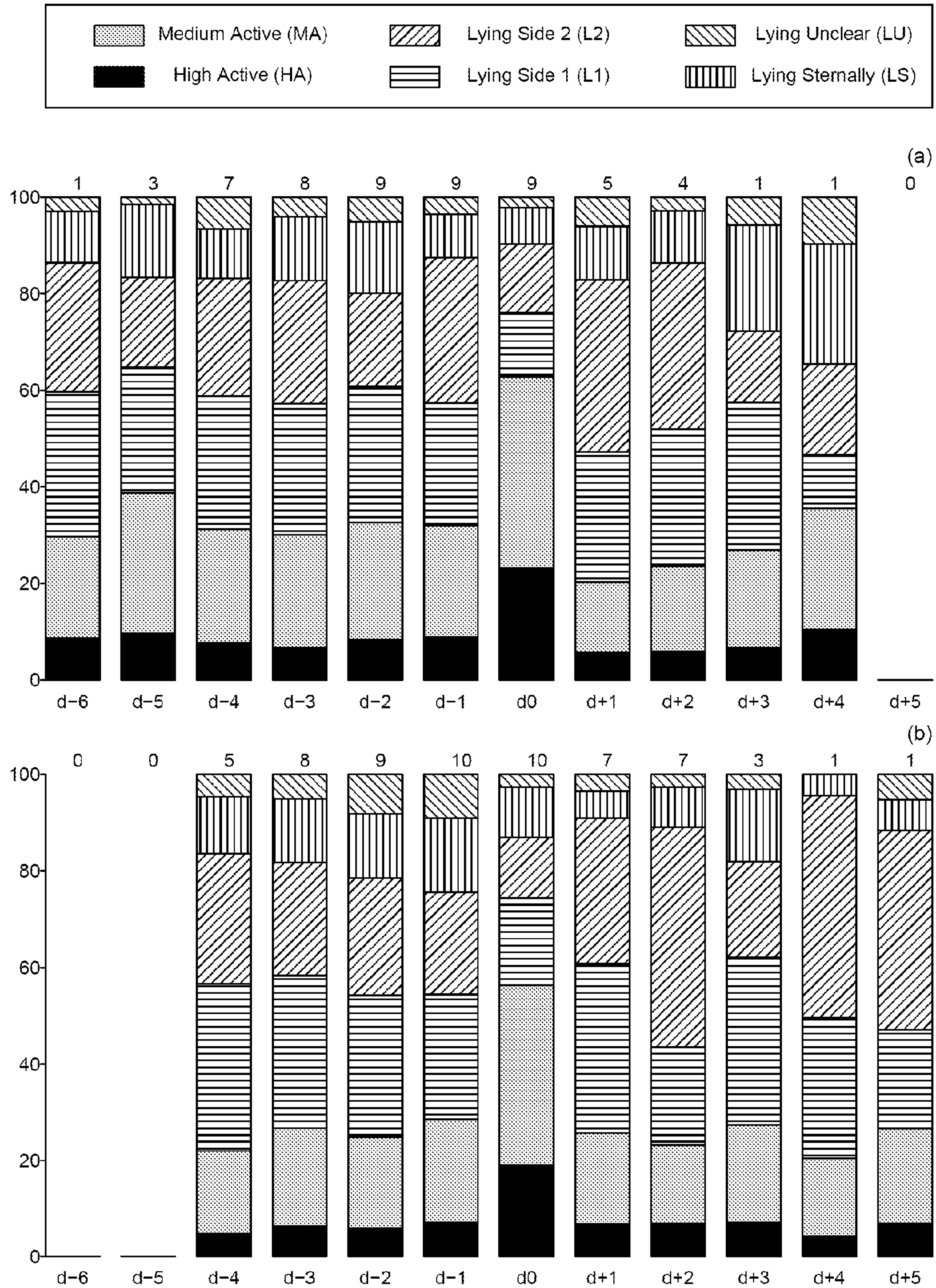
Medium Active (MA)
Lying Side 2 (L2)
Lying Unclear (LU)
High Active (HA)
Lying Side 1 (L1)
Lying Sternally (LS)
(a)
1
3
7
8
9
9
9
5
4
1
1
0
100
80
60
40
20
0
d-6
d-5
d-4
d-3
d-2
d-1
d0
d+1
d+2
d+3
d+4
d+5
(b)
0
0
5
8
9
10
10
7
7
3
1
1
100
80
60
40
20
0
d-6
d-5
d-4
d-3
d-2
d-1
d0
d+1
d+2
d+3
d+4
d+5

Fig. 7

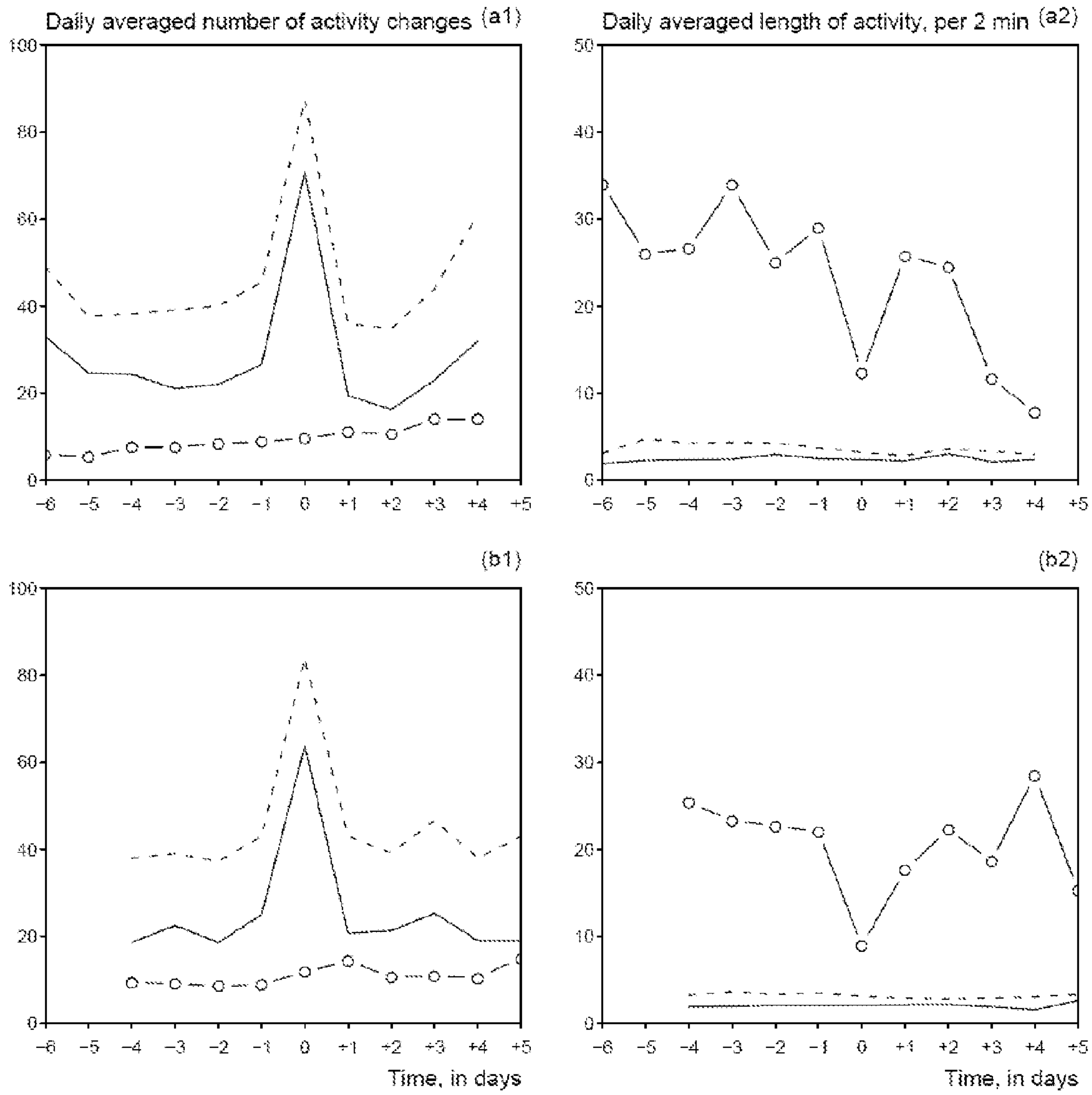
Daily averaged number of activity changes (a1)
Daily averaged length of activity, per 2 min (a2)
(b1)
(b2)
100
80
60
40
20
0
50
40
30
20
10
0
−6 −5 −4 −3 −2 −1 0 +1 +2 +3 +4 +5
Time, in days
Time, in days

Fig. 8

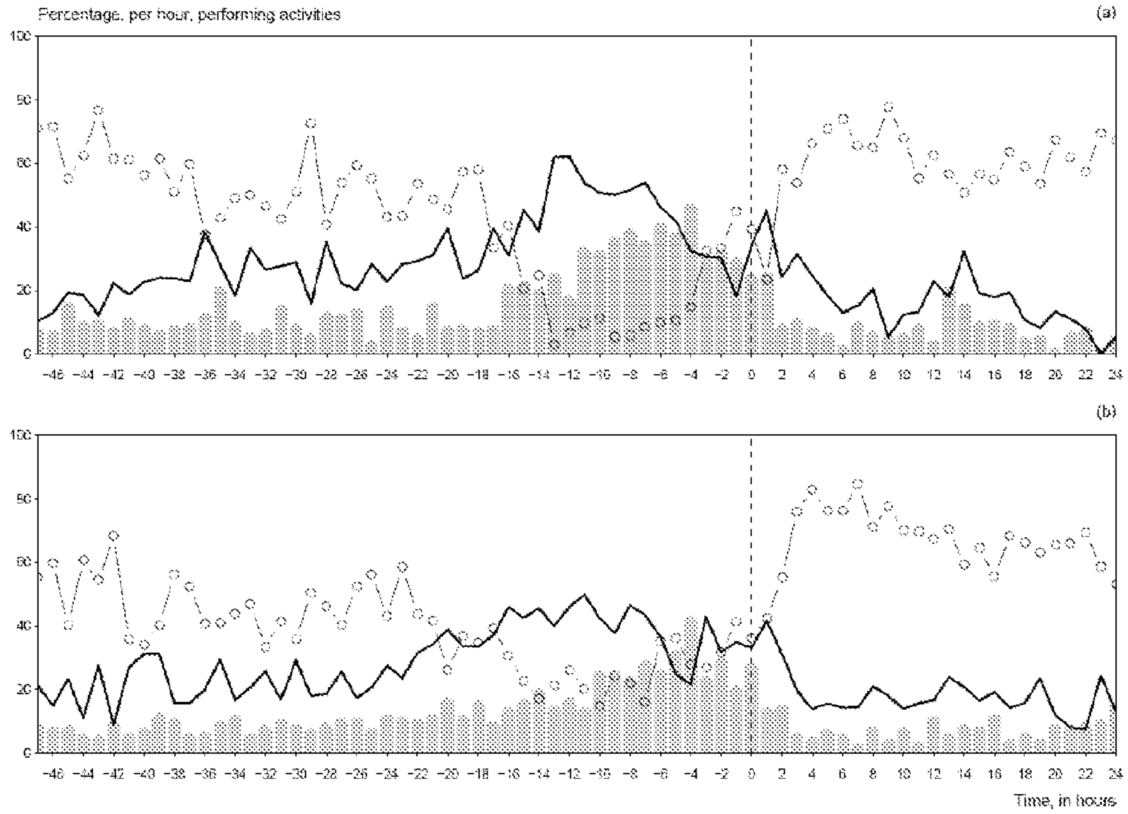
Percentage, per hour, performing activities
(a)
(b)
Time, in hours

Fig. 9

INTERNATIONAL SEARCH REPORT

International application No
PCT/DK2011/050106

A. CLASSIFICATION OF SUBJECT MATTER
INV. A01K29/00 A61D17/00
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
A01K A61D

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practical, search terms used)

EPO-Internal, WPI Data, BIOSIS

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X,P	CORNOU; LUNDBYE-CHRISTENSEN: "Classification of sows' activity types from acceleration patterns using univariate and multivariate models", COMPUTERS AND ELECTRONINCS IN AGRICULTURE, vol. 72, no. 2, July 2010 (2010-07), pages 53-60, XP002638309, the whole document ----- -/-	1-18, 20-26

[X] Further documents are listed in the continuation of Box C.

[ ] See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier document but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art.

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
23 May 2011	01/06/2011

Name and mailing address of the ISA/	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL - 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016	von Arx, Vik

INTERNATIONAL SEARCH REPORT

International application No.
PCT/DK2011/050106

Box No. II Observations where certain claims were found unsearchable (Continuation of item 2 of first sheet)

This international search report has not been established in respect of certain claims under Article 17(2)(a) for the following reasons:

1. ☒ Claims Nos.: 19, 20
because they relate to subject matter not required to be searched by this Authority, namely:
Rule 39.1(iv) PCT - Diagnostic method practised on the human or animal body

2. ☐ Claims Nos.:
because they relate to parts of the international application that do not comply with the prescribed requirements to such an extent that no meaningful international search can be carried out, specifically:

3. ☐ Claims Nos.:
because they are dependent claims and are not drafted in accordance with the second and third sentences of Rule 6.4(a).

Box No. III Observations where unity of invention is lacking (Continuation of item 3 of first sheet)

This International Searching Authority found multiple inventions in this international application, as follows:

1. ☐ As all required additional search fees were timely paid by the applicant, this international search report covers all searchable claims.

2. ☐ As all searchable claims could be searched without effort justifying an additional fees, this Authority did not invite payment of additional fees.

3. ☐ As only some of the required additional search fees were timely paid by the applicant, this international search report covers only those claims for which fees were paid, specifically claims Nos. :

4. ☐ No required additional search fees were timely paid by the applicant. Consequently, this international search report is restricted to the invention first mentioned in the claims; it is covered by claims Nos. :

Remark on Protest

☐ The additional search fees were accompanied by the applicant's protest and, where applicable, the payment of a protest fee.

☐ The additional search fees were accompanied by the applicant's protest but the applicable protest fee was not paid within the time limit specified in the invitation.

☐ No protest accompanied the payment of additional search fees.

International application No
PCT/DK2011/050106

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	CORNOU C ET AL: "Classifying sows' activity types from acceleration patterns", APPLIED ANIMAL BEHAVIOUR SCIENCE, ELSEVIER SCIENCE PUBLISHERS BV., AMSTERDAM, NL, vol. Ill, no. 3-4, 1 June 2008 (2008-06-01), pages 262-273, XP022603775, ISSN: 0168-1591, D0I: D0I:10.1016/J.APPLANIM.2007.06.021 [retrieved on 2008-04-10] cited in the application the whole document -----	1-18, 21-26