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Hidden phase-type Markov model for the prediction of onset of farrowing for loose-housed sows

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ABSTRACT

High piglet mortality is an issue in the pig production. Evidence indicates that if the time of farrowing can be predicted, the mortality can be reduced through planned supervision or improved climate regulation. The aim of the study was to improve the prediction of onset of farrowing by monitoring pre-parturient behaviour of sows using several sensors and by developing an automated system for the prediction of time to farrowing. The resulting prediction model, named as Hidden Phase-type Markov Model (HPMM), assumes that a sow passes through the behavioural states *Before Nest-Building*, *Nest-Building* and *Resting* before reaching the *Farrowing* state. Each state was further split into phases, to allow a more realistic distribution of sojourn times. As these phases and states are unobservable, HPMM was used to calculate the probability of a sow being in given phase using the automatic sensor measures. Thus *time to farrowing* could be predicted at each time point. The prediction algorithm was validated on a sensor data set for about 35 sows, each followed from day 105 (day-105) since mating until the farrowing. Sensors include sow activity measured by video recording as well as by a photo-cell grid, and water consumption. The algorithm was evaluated using heuristic warning strategies e.g. that a warning should be generated when the expected time to farrowing was less than 12 h (inspired by the regulation of floor heating systems). The performance of the sensors was evaluated. Different combinations of sensor types outperformed the use of a single sensor type. Using a combination of water and activity sensors the prediction algorithm gave a coherent warning period prior to farrowing (true warning) in 97% of the cases. The duration from start of the warning period to farrowing had a mean 11.5 (SD = 4.6) h. False warning periods ending before farrowing lasted on average only 0.7 h per sow. The use of HPMM thus allowed a direct prediction of the time to farrowing, handling more than one sensor and a compact representation of historical sensor information.

1. Introduction

Piglet mortality is one of the major causes for economic loss in pig production. An average of 13.7% of the live born piglets died before weaning in Danish sow herds in 2012 according to Vinther (2013). Although the variation between the Danish herds is not well documented, a Norwegian study (Andersen et al., 2007) has documented the mortality rates ranging from 5 to 24% and a Swedish study (Wallgren, 2013) has also discussed the variation between the herds and herd management. Baxter et al. (2011) reviews different studies in this field. The large variability between herds suggests a management component to the mortality, and several studies indicate that it is possible to reduce this mortality, especially in the herds with high mortality, either by increasing the supervision of the farrowings (White et al., 1996; Andersen et al., 2009), or through improved climate regulation during farrowing and the following days (Malmkvist et al., 2006). However, management efforts are only efficient if the required time can be minimised, and this requires that the time of farrowing can be predicted fairly precisely, particularly in large herds where the management effort per animal is often reduced. Based on mating time, the time of farrowing can be predicted within approximately ±2 days and this value is used to a large extent in farm planning. To obtain a better prediction of the time, it is necessary to include observations of the sows prior to farrowing.

Early studies have indicated that it is possible to base predictions on automatically recorded sensor data. These prior studies suggest that the change in the sow behaviour is reflected in change in the pattern of the sensor measurements. Erez and Hartsock (1990) described a system based on photo-cells to monitor

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periparturient activity of sows, and the experiment described by Bressers et al. (1994) showed significant changes in the ear base temperature around farrowing. The temperature increase started between 6 and 12 h before farrowing.

Since these studies, a range of other sensors have become available. Thus a management tool for farrowing prediction can now use the online sensor information including feeding pattern, water intake, temperature or humidity in the pen level, and activity of the animal. For example, Oliviero et al. (2008) have used movement sensors (photocells and a thin-film ferroelectret force sensors) to detect the onset of farrowing in the crates.

The wide range of sensor technology has helped to record a huge amount of data; as a result statistical algorithms are necessary to extract behavioural patterns and combine measurements from multiple sensors into a useful information. Recently several studies have focused on statistical methods for handling data from online measurements. Different techniques have been used to extract the patterns, primarily different versions of the Kalman filter or Dynamic Linear Models (West and Harrison, 1997).

Madsen and Kristensen (2005), Madsen et al. (2005) looked at Dynamic Linear models for monitoring the health condition of young pigs by their drinking behaviour with an emphasis on diurnal drinking pattern. In this study a CUSUM approach based on the V-mask was used for detecting changes in the drinking pattern. Cornou and Lundbye-Christensen (2012) developed two methods to detect the onset of farrowing by monitoring the activity of the sow in the farrowing pen: 1. logistic dynamic generalised linear models for diurnal variation, and 2. modelling of activity using a cumulative sum based on daily variation. The warning signal for onset of farrowing, in either methods of Cornou and Lundbye-Christensen (2012), is based on the detection of change in the activity pattern. The studies show that these changing pattern occurs mostly when the sow starts nest building (Baxter, 1984; Oliviero et al., 2008). However, most managemental tasks such as climate regulation require a direct estimate of time to farrowing. In such cases, the warning signal of Cornou and Lundbye-Christensen (2012) requires additional information about the distribution of the time from change point detection to start of farrowing.

Another promising class of models is that used in the analysis of *time to failure*. These models have so far not been implemented in farrowing prediction. Dayanik and Goulding (2009) gave a framework of detection of the distribution of an unobservable disorder time due to an unobservable cause. This type of model has only been applied in very few cases within livestock production. One such method is to use the Phase-type (PH) distribution for the event *time to failure* (Cox, 1955; Neuts, 1975) or in farrowing context, *time to farrowing*. PH-distributions are a special type of a Markov models in which the time spent in a stochastic process is modelled with phases through which objects in the model progress until the process is absorbed. Thus, in the prediction of farrowing, we would assume that the sow passes through different phases and is absorbed at farrowing. These behavioural phases are unobservable or hidden. However, if the sensor observations recorded on the pen level depend on the current phase of the sow, Hidden Markov Models (HMM) may be used to identify the latent phase. Such a combination with a PH-distribution furthermore gives an easy mechanism for aggregating and storing the information in historical registrations, and can easily handle observations from different types of sensors.

The purpose of this paper is to present and validate a prediction algorithm developed based on the above principles, and to validate the algorithm by applying simple heuristic warning strategies based on the results from the algorithm. The evaluation will compare different combinations of sensor types as input. The strategies include using the expected time to farrowing and the probability of farrowing. The farrowing prediction algorithm is planned to be a part of a farm management information system. The system will automatically collect sensor data and do the necessary calculations to make real-time predictions of farrowings. The real-time part of the algorithm will consist of a continuous revision of the probability distribution over the phases of the HMM based on sensor and farmer observations.

The predictions are based on herd specific parameters describing the distribution of the duration of each state of the farrowing process, as well as the conditional distribution of the sensor observations. The estimation of these parameters is described in chapter 3 of Aparna (2013).

2. Materials and methods

In this section we will present the biological knowledge and principles used in the formulation of the algorithm, comprising the experimental setup and the different sensors used.

2.1. Experimental data

The data used in this study were collected from late 2008 to early 2009 in the experimental farm at the research centre, Foulum, Denmark. 64 sows were introduced to the farrowing pen approximately seven days before expected farrowing. The sows were fed twice a day, 8:00–8:45 and 15:00–15:30, using an automatic feeding system. Management of the pen was restricted to a 2 h period between 8:45 and 10:00, after the first feeding, where the pens were cleaned and 1 kg straw was provided daily on the floor.

Each farrowing pen had a number of sensors installed such as water valve and photo-cells as shown in Fig. 1. In addition, video-recordings of each pen were made from the time when the sow was introduced until after farrowing. Additional visual analysis of these recordings includes identifying the start of farrowing (time of birth of first piglet) as well as a time point when the sow was nest-building. The onset of nest-building was recorded by an experienced observer and was identified based on the criteria described in Malmkvist et al. (2006), as the first occurrence of at least five front leg pawings per hour or repeated carrying of straw, without being interrupted by resting periods longer than 2 h. The actual time of onset farrowing was used to validate the algorithm. The observed nest building time was used to interpret "the spikes of" the prediction curve but not directly for quantifying the algorithm performance.

The different measurements used for the development of the algorithm are described in the following. The data from the sensors were recorded with different time intervals, ranging from seconds to minutes. However, for this paper we consider the data pooled over half an hour intervals. Therefore a maximum of 48 observations were observed per day per sow. The pattern of these observations were used in the specification of statistical models described later on. The water consumption, video-activity and grid-activity data were collected from 45, 64 and 45 sows, respectively. The sensor information collected before 105 days (day-105) after mating were excluded from the study. Some sows were discarded from the study because of failure of sensors. Furthermore, those sows for which data was recorded for less than 3 days before farrowing were also excluded from the prediction. The number of sows used in the study varied from 34 to 55. Sample size for different scenarios of sensor combination are presented together with the results.

2.1.1. Water consumption of sows

The sensor for water consumption measures the water consumed by the sow as the number of rotations of the water valve