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Detection of Oestrus and Lameness in Dairy Cows

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PhD thesis, May 2011

DTU Electrical Engineering
Department of Electrical Engineering

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Ragnar Ingi Jónsson

Summary

This thesis describes studies conducted on the subject of detecting oestrus and lameness in dairy cows.

The studies comprise methods of statistical change detection and model based diagnosis, respectively.

In the case of statistical change detection the development of algorithms for a decision support system is based on identifying behaviour from patterns of normal and deviant behaviour. Signal processing combined with statistical methods, e.g. likelihood ratio tests, are utilized to correlate observed behaviours with normal and detect changes. Diagnosis includes data from the available population of animals in order to isolate patterns of behaviours outside the norm for individuals, while being robust to common disturbance factors. The research is based on methods from change detection and fault diagnosis. Fault diagnosis techniques are employed to reduce the false alarm ratio, and attempts are made to isolate events and artefacts in signals that otherwise can give rise to false alarms.

For the model based diagnosis the diagnosis is generally done evaluating an estimated probability distribution against hypotheses about causes of change behaviour, e.g. oestrus or lameness. The models used for diagnosis are chosen to represent the behaviours. A quantized system description is used as a diagnostic model. This technique is based on automata theory. The methods are in most cases specified to take into account parameters specific to the differences between production systems.

The development of these methods and algorithms is an interdisciplinary activity including methods from fault diagnosis, information technology and statistics.

Resumé

Denne afhandling beskriver studier omkring detektering af brunst og halthed hos malkekøer.

Udviklingen af algoritmer til en første version af et system til udpegning af udsatte dyr er baseret på at identificere adfærd fra mønstre for normal og afvigende adfærd. Signalbehandling kombineret med statistiske metoder, fx likelihood ratio test, der korrelerer observeret adfærd med normal og detekterer ændringer. At diagnosticere data fra de tilgængelige data for at isolere mønstre for adfærd uden for normen for den enkelte og samtidig være robust overfor fælles ikke-normale faktorer for forstyrrelser. Studierne er baseret på metoder fra change detection og fejldiagnose. Fejldiagnose teknikker, til at reducere antallet af falske alarmer, og forsøg gøres for at isolere hændelser og artefakter i signaler, som ellers kan give anledning til falske alarmer.

Diagnosticeringen udføres ved at evaluere en anslået sandsynlighedsfordeling mod hypoteser om årsagerne til den ændrede adfærd, f.eks oestrus eller halthed. De modeller, der anvendes til diagnosticering er valgt til at repræsentere adfærd. En kvantiseret system beskrivelse benyttes som et diagnostisk model. Denne teknik er baseret på automata teori. Metoderne er i de fleste tilfælde er fastsat til at tage hensyn til parametre der er specifikke for forskellene mellem produktionssystemer.

Udviklingen af disse metoder og algoritmer er en tværfaglig aktivitet, herunder metoder fra fejldiagnose, informationsteknologi og statistikker.

Preface

This thesis is written as a partial fulfilment of the requirements for the Ph.D. program in engineering. The Ph.D. project was conducted at the Technical University of Denmark, Department of Electrical Engineering. The project was carried out from April 2007 to July 2010 founded by 1/3 of a DTU scholarship and 2/3 of a research grant from the Danish Research Agency, contract no. 2106-05-0046. The supervisors of the project were (main supervisor) Professor Mogens Blanke, Associate Professor Niels Kjølstad Poulsen at the Department of Informatics and Mathematical Modelling and Senior Scientist Søren Højsgaard at Department of Genetics and Biotechnology, Aarhus University.

The thesis constitutes a collection of papers which have been submitted for conferences and journals during the project. Since the papers represent work carried out over a three year period, a consistent nomenclature has not been possible.

<div align="right">

Ragnar Ingi Jónsson
Copenhagen, May 2011

</div>

Dissemination of Results

Papers included in the thesis

[A] Jónsson, R. I., Björgvinsson, T., Blanke, M., Poulsen, N. K., Højsgaard, S. and Munksgaard, L. Oestrus Detection in Dairy Cows Using Likelihood Ratio Tests. *In Proceedings of the 17th World Congress, The International Federation of Automatic Control, 658-663*, Seoul, Korea, 2008. Published

[B] Jónsson, R., Caponetti, F., Blanke M. and Poulsen N. K. Oestrus Detection in Dairy Cows using Automata-Based Modelling and Diagnosis. *In Proceedings of SafeProcess 2009: 1402-1407*, 2009, Barcelona, Spain. Published

[C] Jónsson, R. I., Blanke, M., Poulsen, N. K., Munksgaard, L. and Højsgaard, S. Combination of activity and lying/standing data for detection of oestrous in cows. *In Proceedings of Joint International Agricultural Conference JIAC'09: 207-214*, 2009, Wageningen, Netherlands. Published

[D] Jónsson, R., Blanke M., Poulsen N. K., Caponetti, F. and Højsgaard, S. Oestrus Detection in Dairy Cows from Activity and Lying Data using on-line Individual Models. *Computers and Electronics in Agriculture*, 76(1),6–15,2011. Published

[E] Jónsson, R., Munksgaard, L., Caponetti, F., Poulsen N. K., Blanke M. and Højsgaard, S. On-line detection of lameness in dairy cows. *Journal of Dairy Science*, 2011. Submitted

Other publications

Jónsson, R. Modelling Cow Behaviour Using Stochastic Automata. *Technical Report 2010.03, Ruhr-Universität Bochum, Lehrstuhl für Automatisierungstechnik und Prozessinformatik*, 2010, Bochum, Germany. Published

Zarchi, H. A., Jónsson, R. I. and Blanke, M. Improving Oestrus Detection in Dairy Cows by Combining Statistical Detection with Fuzzy Logic Classification. *In Proceedings of the 7th Workshop on Advanced Control and Diagnosis*, Zielona Gora, Poland, 2009. Published

Acknowledgements

Contents

CHAPTER 1

Introduction

This thesis addresses the subject of automatic detection of oestrus and lameness in dairy cows. The detection of oestrus involves assessment of the cow's reproduction state with focus on conceiving the cow in order to maintain production of milk. The detection of lameness deals with discovering when a cow is experiencing discomfort in a leg or a hoof for the purpose of initiating early treatment of the illness.

1.1 Motivation and aim

The structural development in dairy farming has led to increased farm size where each co-worker is responsible for monitoring an increasing number of animals. Furthermore, housing has changed from tie-stalls to loose housing systems, where observations of individual animals are more complicated. At the same time there is an increasing focus on animal health and welfare. This has the consequence that greater manual labour is needed if assessment of health and reproduction state is to be performed manually. With growing farm size and the ever so existing wish for reducing production cost, methods for automatically assessing the reproduction and health state of each cow becomes more and more important. Automatic registration of behaviour can contribute considerably to on-farm assessment of animal welfare as well as a tool for consultancy, and can be used as documentation for a given standard of animal welfare.

1.1.1   Reproduction state

On a commercial dairy farm it is important that the reproduction is high. To maintain a high production level for each cow the cow has to give birth to a calf on regular basis as the milk production is highest in a period after each calving. Conception in dairy farms is usually performed by artificial insemination (AI). For an artificial insemination a sperm from a bull is stored and injected into the cows uterus in connection with oestrus if the cow should become pregnant (Webb [2003]).

Each time an oestrus case is missed approximately 3 more weeks pass before the cow can be inseminated again. This means prolonging the period before the cow reaches maximum production again, which again means increased costs in feeding with respect to milk production, i.e. reduced efficiency.

1.1.2   Health

Being able to insure the well-being of as many cows as possible at all times is important, both from an ethical point of view and from an economical point of view. From the ethical point of view it is important that the animals feel as well as possible and that they are spared of discomfort and pain.

Well-being of the cows also affects the economical point of view from at least 3 different directions. First is that animals that are not feeling well are likely to be eating less, which again affects the milk production, as there for a dairy cow is a direct link between the feed intake and the milk production. The second is that conception in a lame cow is more than 40 days delayed with respect to healthy cows (Dobson et al. [2008]). The third is that consumers are becoming more aware that they do not want to purchase products unless they feel convinced that the product is produced under ethically responsible conditions.

1.1.3   Aims

The aims of the Ph.D project were analysis and development of new competitive and robust methods for early detection of deviant behaviour in cows. More specifically to assess cows reproduction status by detecting oestrus and to assess cows health in the form of lameness. The work was expected to result in detection methods and algorithms with emphasis on large scale applications and the use of low-cost sensor equipment.

1.2   Document structure

This thesis comprises a collection of papers, preceded with introductory and concluding chapters.

Chapter 1 contains descriptions of the motivations and aim, explains the oestrus and lameness phenomena in dairy cows and states a selection of the earlier results on the subject of automatic detection of oestrus and lameness.

Chapter 2 contains a description of the research stable, from where the observations, that form the basis of the behavioural assessment, originate from. This chapter also describes the data which were available for the study.

Chapter 3 establishes the link between the different papers included in the last part of the thesis.

Chapter 4 contains the conclusions and Chapter 5 contains summaries of each of the papers that are included.

Finally the papers are organised as Paper A to E.

1.3   Oestrus

Oestrus is the phase in a cows ovulation cycle when the cow is sexually receptive. When a cow is in oestrus it is the right time to inseminate the cow in order to conceive the cow (Webb [2003]).

The period from parturition until first oestrus is varying between types of cattle and between parturition. According to Crowe [2008], dairy cows generally ovulate the first post-partum dominant follicle after ~ 15 *days* provided that the cows are sufficiently nourished. The first post-partum ovulation is usually not associated with the expression of oestrus and is followed by a short 9-11 days cycle where the cows most often begin to show signs of oestrus, Crowe [2008]. After that it goes into oestrus with certain interval until pregnancy occurs. Holstein post-partum dairy cows have a 18-23 days cycle, Crowe [2008]. Correct identification of the oestrus is of a huge importance for the farmer as the correct time for insemination occurs in a short period following the oestrus.

When considering behaviour, the expression of oestrus is quite varying and there are many signs of oestrus of different importance. The most evident visual

sign of oestrus is the standing oestrus, where a cow stands to be mounted by other cows or by a bull without appearing to avoid the contact. This evidently clear sign of oestrus was by Roelofs et al. [2005b] shown to occur in 58% of oestrus periods and van Eerdenburg et al. [2002] found that standing oestrus was displayed in 50% of the oestrus cases. Other visual behavioural signs are e.g. sniffing, chin resting and mounting other cows in the herd (Roelofs et al. [2005b]). Of the three latter signs mounting is clearly the most accurate sign of oestrus (Roelofs et al. [2005b]). The failure to express standing oestrus amongst a large portion of the cows as well as the growing size of each production unit has made traditional visual observation of the herd for oestrus identification less efficient. It can no longer be considered as a desirable method for this task. The use of wireless sensors to assess the behavioural expression has therefore become much more attractive. Increased physical activity is monitorable by motion sensitive sensors and the variation in physical activity is one indicator of oestrus. Kiddy [1977] found that on average, the activity at oestrus was about 4 times the normal level. Schlünsen et al. [1987] found that step activity in loose housing with cubicles doubled during oestrus.

According to Roelofs et al. [2005b] it is difficult to assess the correct time for artificial insemination from observing the cows behaviour. The author stated that although accurate time for onset or end of oestrus could be established the correct time for artificial insemination could not be accurately assessed as the variation in time between onset and end of oestrus and ovulation is simply too large between animals.

Foote [1979] investigated the most suitable timing of insemination with respect to the time of discovered oestrus. The author found that for cows and heifers that were identified in oestrus in the morning there was not a significant difference in the conception rate as long as the insemination was performed on the same day. Performing the insemination the next morning was too late. He also stated that cows that were discovered in oestrus in the evening should be inseminated by noon the morning after.

Furthermore, conditions for identification of oestrus and successful artificial insemination have become more difficult in recent years due to reduced expression and decreased duration of oestrus (Dobson et al. [2008]).

Dobson et al. [2008] state that it is becoming more difficult to detect oestrus. They stated that the animals that do not avoid being mounted have declined from 80% to 50% and that the duration has gone from $15h$ to $5h$ during the past 30 to 50 years.

1.4   Lameness

Lameness is a term that covers a group of locomotion disorders in cows. Lameness can be caused by a number of factors such as lesions, injuries, diseases and other factors. Lameness is undesirable as it is associated with pain or some sort of discomfort for the cow (Beusker [2007]). In modern farming it is desirable that animals feel as well as possible. Another important aspect is that a cow that is suffering from lameness will produce less milk than a healthy cow (Hernandez et al. [2005]). Other economical factors worth mentioning are poorer reproduction, costs of treatment associated with occurrence of lameness (Ettema and Østergaard [2006]) and higher probability of cows being prematurely removed from the population (Booth et al. [2004]).

The growing farm size and thereby a demand for more surveillance and the fact that dairy producers often fail to detect lame cows (Whay et al. [2003]) are factors of encouragement for development of methods for automatic lameness detection.

Espejo et al. [2006] found that in randomly selected farms in Minnesota with free-stall high-production group pens, 24.6% of the cows were clinically lame.

When the cow is suffering from lameness the discomfort and pain it experiences may cause the cow to use other postures, walk differently and to have a different behavioural pattern.

The externally visual signs of lameness are first and foremost to be found in the posture of a cow and in the way the cow moves. When a cow is affected by lameness the spine may become arched instead of level, as in a healthy cow. The lame cow will also start to place the legs in a different way than a healthy cow when walking (O'Callaghan [2002]). The changes in postures and gait are much more complex than listed here. A more comprehensive description can be found in e.g. O'Callaghan [2002].

In the literature there exist vast amount of material describing which changes in behaviour are to be expected when a cow becomes lame (Hernandez et al. [2001], Warnick et al. [2001], Kocak and Ekiz [2006], Borderas et al. [2008], Walker et al. [2008]). Mazrier et al. [2006] found that activity was affected by lameness. Gonzalez et al. [2008] investigated changes in short term feeding behaviour in connection with lameness and found that the daily number of visits to the feeding boxes as well as the daily feeding time were reduced when a cow was suffering from lameness. They also found that the feed intake rate, i.e. the weight of feed intake per time unit, increased during lameness.

Table 1.1: Hypotheses about changes in behaviour as symptoms of lameness. A change where an increase is expected is marked with $+$ and $-$ if a decrease is expected.

Behaviour	Trait	Change
Activity	walking	$-$
	lying time	$+$
Feeding	duration	$-$
	time between	$+$
	feed intake rate	$+$
Milking	milk yield	$-$
Other	ovarian cycle	delayed cyclicity

Table 1.1 provides a list of some relevant behavioural symptoms of lameness.

For manually addressing severity of lameness, lameness scoring systems are used (see e.g. Whay [2002], Thomsen et al. [2008]). Many of the scoring systems are comprised of a 5-point scoring scale. Data from such a lameness scoring system are used in this study and described in further details in Section 2.7.

1.5 Contributions

The contributions of the work that is described in this thesis consists of new methods for detecting oestrus and lameness in dairy cows.

A new algorithm for oestrus detection using both observations of activity and lying behaviour is derived, both unsing solely the activity and also combining the activity and the lying behaviour. The algorithm is an on–line algorithm that recursively estimates all necessary parameters. That way no prior estimation or training is needed for initiating the algorithm.

Diurnal variations of the activity is modelled and used to extract the variations in the signal on account of changes in the behaviour without having the diurnal variations to obscure the picture.

A quantity describing the cows' motivation for lying down, called the *lying-balance* was derived and used for the oestrus detection.

Methods for detecting lameness in dairy cows using low cost sensor data are developed.

1.6 Literature overview

This section gives an overview of earlier results for automatic detection of oestrus and lameness. An overview of results in oestrus detection and the detection of lameness are given in the sections below (Section 1.6.1 & Section 1.6.2).

The quality of detection are by tradition in this field done using three quality measures. They are defined as follows:

- *Sensitivity* indicates the number of successful detections and is found as

$$sensitivity = \frac{tp}{tp + fn},$$ (1.1)

  where tp (true positives) is the number of successful detections and fn (false negatives) is the number of missed detections.

- *specificity* indicates the number of false detections and is found as

$$specificity = \frac{tn}{tn + fp},$$ (1.2)

  where tn (true negatives) is the number of correctly classified observations during normal behaviour and fp (false positives) is the number of false detections.

- *Error ratio* indicates the ratio of false detections with respect to the total number of detections. The *error ratio* is calculated as

$$error\ ratio = \frac{fp}{tp + fp}.$$ (1.3)

  The *error ratio* is in the literature often referred to as *error rate*.

1.6.1 Results in oestrus detection

Numerous studies have been conducted on the subject of detection of oestrus in dairy cows. Methods of automated oestrus detection has been reviewed by Eradus and Jansen [1999] (Eradus and Jansen [1999] dealt with animal identification and monitoring), Nebel et al. [2000] and Firk et al. [2002]. Comparisons of commercial oestrus detection systems have been carried out by Cavalieri et al. [2003] and Peralta et al. [2005].

Studies on automatic detection of oestrus in dairy cattle by measurements of physical activity has been carried out by many (Table 1.2).

Moore and Spahr [1991] compared the most recent 12 h of activity with a baseline activity level from the same 12 h period during the previous 3 d.

Liu and Spahr [1993] calculated every 2 h a 12 h mean for the preceding 12 h and divides that mean activity with the mean activity in the same 12 h of the day, as the test period, in the 2 d immediately prior to the test period.

Koelsch et al. [1994] tried different statistical methods to detect oestrus by means of activity measurements. The decision algorithm compares the "Test Day" (current day) to the "Base Line Period", a set of days prior to the test day. Both running average, and Finite Interval Response (FIR) low pass filter, were tested. Best results, of the test detected 72% of the oestrus periods while having 0-1 false detections for each oestrus period. A modification of the algorithm where conditions on statistically unique time duration of elevated activity was added to the condition of statistically unique activity level, resulted in detection of 79% of the oestrus periods and a specificity of 98%.

Mol et al. [1997] described results from detection of oestrus and diseases by means of time series analysis of various traits combined with a Kalman filter. The traits included activity, milk yield, milk temperature, electrical conductivity of milk and concentrate leftovers. Experimental data for these traits was collected at two experimental farms in the Netherlands in 1993 and 1994. The data consisted of measurements recorded at each milking (two times a day). The activity as well as yield, milk temperature and milk conductivity was modelled with a time series model while the concentrate leftovers were described with a probability distribution. The parameters in the time series model were updated at each milking with a Kalman filter. At each milking, a deviation between the activity measurements and a prediction from the Kalman filter was calculated. If the error fell outside of a confidence interval (the error was assumed to have a normal distribution) an alarm was initiated.

Alarms could be initiated either as single alerts, e.g. deviant activity, or as combined alerts. A combined alert was initiated where a combination of more than one trait fell outside of a confidence interval. An oestrus alert, resulting from a combined alert, was given when the activity was rather high and the sum of standardised errors of activity, yield and temperature fell outside of a certain confidence interval. When looking at the results for e.g. oestrus detection for alerts based solely on measurements of activity, one can bare in mind that a sensitivity of 91.2% and specificity of 95.6% are not necessarily very describing for the result as there were 435 true positive alerts and 1619 false positive alerts during 41803 milkings.

Maatje et al. [1997] address both detection of oestrus and mastitis. Oestrus detection was realized by means of activity measurements and the authors focused on predicting the onset time of oestrus. The activity was measured with mercury switches on the cows legs. A cow was assumed to be indicated for oestrus when the number of step counts was twice the basal number of steps of that cow. This experiment gave a detection rate of 78% and a fault rate of 32%.

In the last sections of the article the authors described methods of oestrus detection by means of combined traits. This is the same experiment and algorithm, as those described in Mol et al. [1997] and Mol et al. [1999].

Eradus et al. [1999] described oestrus detection by means of a fuzzy inference system. The traits used were; relative cow activity, milk temperature and milk production. Later, in an optimisation process, the cyclic nature of oestrus was also considered, mainly to reduce the number of false alarms. The obtained results were as following: 1. Before optimisation: detection rate = 79%, false rate = 66%, 2. After optimisation: detection rate = 83%, false rate = 48%.

Mol and Woldt [2001] extended the time series model from Mol et al. [1997] and Mol et al. [1999] with a fuzzy inference system. The data used for testing of oestrus detection algorithm were the same as was used in Mol et al. [1997], Mol et al. [1999] etc.. The goal was to reduce the number of false positive alerts without reducing the number of true positive alerts. The fuzzy logic model incorporated other information into the model and worked as an extra decision making tool. The fuzzy logic model treated alerts from the time series model and classified them into true or false, based on further information from the management system (reproduction data etc.). As the fuzzy logic system acted as an extra classificator on alerts from the time series model, the number of true positive alerts can not be increased by this means; but the number of false positive alerts can possibly be reduced. The additional information consisted of: reproductive status (calved, in heat, inseminated or in calf), number of cows with alerts and the strength of alert.

Firk et al. [2003b] treated both univariate analysis of traits, as well as multivariate analysis. The univariate analysis included analysis of activity, milk yield, milk flow rate and electrical conductivity. One activity measurement contained activity value obtained by reading a mercury pedometer at each milking (milking twice a day). Activity was analysed by means of a moving average with a history of 10 values, a day to day comparison, exponential smoothing and Box-Jenkins three parameter smoothing. The actual activity measurement was compared to the prediction value, calculated by means of one of the above mentioned methods. If the activity value exceeded the prediction value by more than a predefined threshold, the cow was considered in oestrus. The four methods were tested, and the moving average with a history of 10 values gave the

best results, regarding sensitivity and error rate. The multivariate approach was realized by a fuzzy logic model. The inputs to the fuzzy logic model consisted of the rate between the actual measurement and prediction value. The fuzzy logic model was tested on single up to four traits.

Firk et al. [2003a] built further on Firk et al. [2003b]. The authors were studying the potential benefit of combining the traits activity and period since last oestrus. These two traits were combined in a fuzzy logic model, that had the inputs relative deviations of activity (that is deviations from a moving average over 10 values) and the period between the actual observation and last oestrus or insemination. The ability to detect oestrus therefore became dependent on the ability to find previous (the first after calving) oestrus cases.

Roelofs et al. [2005a] investigated whether the number of steps for each 2 hours could be used as a tool for oestrus detection and as a predictor for time of ovulation. For oestrus detection, commercial pedometers were used, and placed on the cows' front leg. The pedometer recorded the number of steps over 2h periods. Approximately 18 days of pedometer measurements around behavioural oestrus were analysed for animals that showed visual signs of oestrus. Oestrus was detected using two methods; median number of steps and standard deviation of the average number of steps.

In the median method, the actual 2h measurement was divided by the median of the 10 preceding days, for this particular 2h period of the day. The threshold was 10 for one period or 5 for two consecutive periods.

In the standard deviation method, the actual 2h measurement was compared to the mean and standard deviation of the number of steps was calculated for the 10 preceding days. If the actual measurement exceeded a threshold of a predefined number of standard deviations, an oestrus alert was initiated.

Friggens et al. [2008] used measurements of milk progesterone to detect oestrus. The progesterone profile was smoothed by means of an extended Kalman filter. If the smoothed progesterone measurement went below a threshold value, the cow was assumed in oestrus. For this to be possible the cow had to be in the state *oestrus cycling*, which was detected if two consecutive smoothed progesterone measurements exceeded a threshold. The authors used two different measures for known oestruses: 1) confirmed oestrus, where the insemination was followed by a positive pregnancy test and; 2) ratified oestruses, where the progesterone profile was used to identify oestruses where the cow was not inseminated. Further description of the definitions for the known oestruses can be found in Friggens et al. [2008]. The model detected 93.3% of ratified oestruses (assumed oestruses) with a specificity of 93.7%. The model detected 99.2% of confirmed oestruses without stating associated specificity.

O'Connell et al. [2011] combined measurements of milk progesterone level and activity. Diurnal variations in the activity were modelled and compensated for using a Holt-Winters seasonal model. The detection model comprised a hidden semi-Markov model in two versions either considering only activity or activity and progesterone. When using only activity the model had a sensitivity of 70.8% and an error rate of 14.2%. They stated by including also progesterone measurements the number of false positives could be reduced.

Table 1.2: Articles on oestrus detection by means of activity or by activity and combination of other traits

Author	Traits	Algorithm	Results
Williams et al. [1981]	Activity	Increase in mean value	Sensitivity 68-74% Error rate 17-42%
Schofield et al. [1991]	Activity	Increase in mean value	Sensitivity 100% Error rate 33%
Moore and Spahr [1991]	Activity	Increase in mean value	Sensitivity 55% Error rate 21%
Pulvermacher and Maatje [1992]	Activity	-	Sensitivity 78% Error rate 51%
Eradus et al. [1992]	Activity	Relative increase comp. to earlier meas.	Sensitivity 82% Error rate 51%
Redden et al. [1993]	Activity	Comparison of mean values	Sensitivity 80% Error rate 17%
Liu and Spahr [1993]	Activity	Comparison of mean values	Sensitivity 74% Error rate 33%
Koelsch et al. [1994]	Activity	Statistical test	Sensitivity 79% Specificity 98%
Wendl and Klindtworth [1997]	Activity	Comparison of mean values (7d mean)	Sensitivity 73-86% Error rate 42-55%
Mol et al. [1997]	Activity	Analysis of time series. Parameters updated by a Kalman filter. Confidence interval of various values as threshold.	Sensitivity 81-91% Specificity 98-96 %
Mol et al. [1997] and Mol et al. [1999]	Activity, milk yield, milk temp., electrical conductivity,	Analysis of time series and prob. distribution. Parameters updated by means of a Kalman	Sensitivity 83-94% Specificity 98-95%

Author	Traits	Algorithm	Results
	concentrate leftovers	filter. Confidence interval used as threshold.	
Maatje et al. [1997]	Activity	Increase in mean value	Sensitivity 78% Error rate 32%
Maatje et al. [1997]	Similar to Mol et al. [1997]	Similar to Mol et al. [1997]	Sensitivity 87% Specificity 97%
Eradus et al. [1999]	Activity, milk temp., milk yield	Fuzzy inference system	Sensitivity 79-83% Error rate 48-66%
Mol and Woldt [2001]	Activity, milk yield, milk temp., electrical conductivity, concentrate leftovers, management system data	Similar to Mol et al. [1997] Detection model extended with fuzzy logic model, that includes data from management system	Sensitivity 67-71% Specificity 99%
Firk et al. [2003b]	Activity	Threshold on deviation of the actual activity measurement from a prediction value.	Sensitivity 71-94% Error rate 21-53%
Firk et al. [2003b]	Activity, milk yield, milk flow rate, electrical cond-activity	Fuzzy logic model. Inputs consisted of rates between the actual measurements and a prediction value calculated by a moving average.	Sensitivity 87-88% Error rate 28-31%
Firk et al. [2003a]	Activity, days from last oestrus	Fuzzy logic model. Inputs consisted of the rate between the actual activity and its prediction value and days from last oestrus	Sensitivity 88% Error rate 13%
Roelofs et al. [2005a]	Activity	Increase in mean value and statistical test	Sensitivity 51-87% Error rate 5-40%
Friggens et al. [2008]	Progesterone	Extended Kalman filter	Sensitivity 93% Specificity 94%
O'Connell et al. [2011]	Activity	Hidden semi-Markov model	Sensitivity 71% Error rate 14%

1.6.2 Results in lameness detection

Automatic lameness detection has been addressed in several studies. There are mainly two approaches that have been used for the detection of lameness namely behaviour assessment and gait assessment. In the first one the focus is on general behaviour in terms of e.g. activity, feeding, milking and so forth. In the latter one attempts are made to assess the cows' gait, i.e. the pattern of movement of the limbs.

1.6.2.1 Behaviour assessment

Mazrier et al. [2006] used a simple activity detector to detect lameness. The authors used pedometer data from a leg attached sensor that reports average number of steps per hour since last milking. The authors set the system to daily identify cows that had average number of steps per hour during the last day that was 5% less than the average number of steps per hour during the preceding 10 days. The authors found that of cows with recorded clinical lameness 55.3% had at least 5% reduction in average number of steps per hour. Another alarming result was that 54.3% of the cows that had at least a 5% reduction in average number of steps per hour did not develop clinical lameness and were therefore false positives. The system could therefore not be assumed to work sufficiently.

Changes in short-term feeding behaviour of dairy cows in connection with lameness were investigated in Gonzalez et al. [2008]. The changes in short-term feeding behaviour were investigated with respect to the applicability as early indicators of the disease. The authors found that daily feeding time was the parameter that changed most consistently with respect to the different types of lameness studied. A detection algorithm that was set to identify cows with a daily feeding time that was shorter than the average of the daily feeding time during the past seven days minus 2.5 standard deviations was able to detect more than 80% of cows at least one day before manual detection by farm employees.

In Kramer et al. [2009] a fuzzy logic model for classification of lameness and mastitis in dairy cows was developed. The authors included the traits milk yield, dry matter intake, dry matter intake behaviour, water intake, activity and information about preliminary diseases, in their investigations. The best results for lameness detection were obtained using the traits, dry matter intake, feeding time, number of feeding visits, activity and preliminary cases of lameness in the actual lactation. The authors reported that the algorithm was able to detect 75% of the lameness cases with an error rate of 98.3%. Although the sensitivity

or detection ratio is acceptable the number of false alarms or error rate is much too high for the algorithm to be considered applicable in real applications.

1.6.2.2   Gait assessment

When assessing lameness using gate assessment the focus is on detecting deviations in movement pattern, e.g. deviation in step length, attempts to reduce weight on legs and swinging legs while walking.

In Rajkondawar et al. [2002] and Rajkondawar et al. [2006] two parallel force plates were used to measure limbs ground reaction forces when cows walked over the plates. The authors utilised different models and came to a conclusion that the system was sufficiently accurate to use in a commercial application. In Rajkondawar et al. [2002] the authors stated that the system was able to recognise lame cows and identify limbs affected by lameness. The test was performed using only three lame cows and three healthy cows. In Rajkondawar et al. [2006] the logistic regression models were developed for the detection of lameness using measurement limbs ground reaction forces. The system showed promising results and the authors claimed that the methods could result in automated methods for lameness detection by further development.

In Pastell et al. [2006] four strain gauge balances installed into a milking robot were used to measure the load of each leg, number of kicks and total time in the milking robot. The authors observed the changes in data and concluded that limb and hoof disorders can be detected using the system. In Pastell et al. [2008] the authors presented data acquisition and algorithms for detecting leg problems, but stated that there were to many false alarms (Pastell and Kujala [2007]). Pastell and Kujala [2007] improved the algorithm by introducing a neural network model for classification of cows into groups of lame and sound cows respectively.

In Flower et al. [2005] and Flower and Weary [2006] cows wearing reflective markers on each leg walked along a 40 m test alley after morning milking for 7 consecutive days and were recorded with a video camera. The video recordings were analysed with image processing software and the authors stated that the method showed distinct differences between cows with no visible hoof pathologies and those with painful injuries but more detailed analysis was needed to decide whether the method was usable for early detection of lameness.

In Song et al. [2008] the authors also used vision techniques to detect and predict lameness in dairy cows. The equipment extracted hoof location from images of cows freely passing a video recording device in a narrow pathway of

9 m length. The method's validity was shown by calculating correlation between the automatically calculated hoof trackway and visual locomotion scores. The authors stated that the method has great potential for use in detection and prediction of lameness in dairy cattle.

CHAPTER 2

Available behavioural observations

All of the data used in the studies described in the following originate from the Danish Cattle Research Centre (DCRC) in Foulum, Denmark. The DCRC is a research facility of which main unit is a dairy cow stable that is a loose housing system with cubicles and automatic milking system (DeLaval, Tumba, Sweden). The herd at the DCRC has approximately 150 cows of the breeds Holstein, Red Danes and Jersey. The Holstein cows and the Red Danes are divided into 2 groups with separated milking systems (milking robots) and the Jersey cows are in a separated group also with a separated milking system. The cows have ad libitum access to the milking systems and feeding boxes.

The data consist of measurements of 1) activity; 2) lying behaviour; 3) feeding behaviour; 4) data from automatic milking system (AMS); 5) manually performed oestrus assessment and 6) manually performed lameness scoring. In addition there is access to all relevant logs on each cow. The logs contain information on diseases, medication, calving, insemination as well as other parameters that are not used in this research.

As the data are recorded by means of equipment that occasionally can malfunction, missing data and artefacts occur. Problems associated with missing data and data artefacts are dealt with within the scope of each of detection algorithms that are described in Papers A to E.

Figure 2.1: The research stable at the Danish Cattle Research Centre.
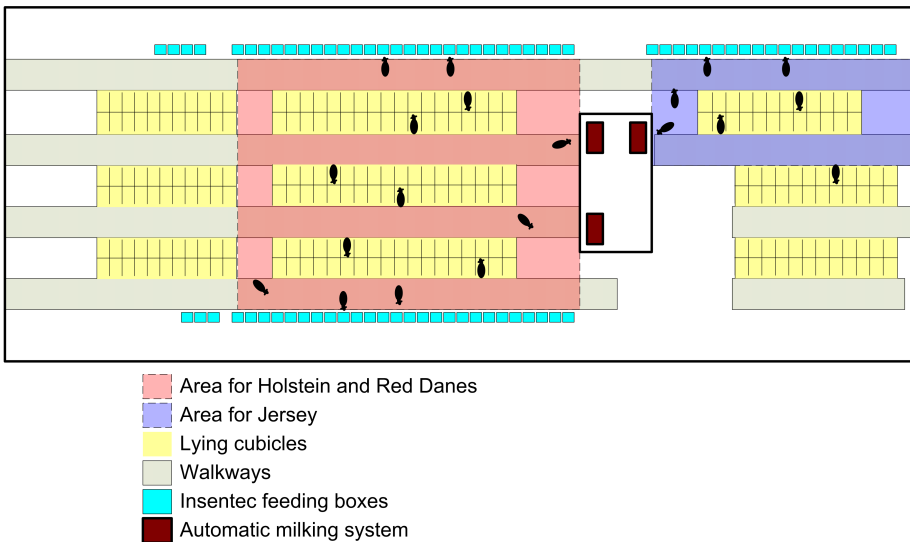
Figure 2.2: A drawing of the research stable at the Danish Cattle Research Centre (DCRC).

Figure 2.1 shows a picture of the stable at the DCRC and Figure 2.2 shows a drawing of the stable.

2.1 Activity

The activity data consist of measurements of activity on the dairy cows in the DCRC. Measurements of activity were available from two different types of sensors in the project period.

The first type is an activity tag that was attached to the cows collar on all cows in

Figure 2.3: The ALPRO® activity tag (the blue device on the side of the necklace).

the stable producing an activity index for each hour. These activity tags were of the type ALPRO® produced by DeLaval, Tumba Sweden. The ALPRO® activity measurements were by default recorded for all cows in the areas where there was free access to the milking systems. The activity observations of the ALPRO® were available throughout the whole project period. Figure 2.3 shows a picture of one activity tag.

The other type of activity measurement was recorded by the IceTag3D®. The IceTag3D® serves multiple behaviour assessment purposes and is therefore described in an independent subsection, in Section 2.5.

2.2   Lying behaviour

As in the case of the activity, recordings of the lying behaviour were also available from two measuring devices. On one hand, data were available from a new measuring device under development which in the following is referred to as the *leg sensor*. On the other hand, recordings of the lying behaviour were available from the previously mentioned IceTag3D®. For both devices applies that the device is attached to the cows leg with a strap (usually a hind leg).

The data sets for the lying behaviour contains measurements of two states namely the states lying/standing. Both the *leg sensor* and the IceTag3D® estimate the lying/standing status from the leg angle. If the leg is in vertical position the cow is assumed to be standing and if the leg is in horizontal position the cow is assumed to be lying.

The *leg sensor* is described below and the IceTag3D® in Section 2.5.

Figure 2.4: A *leg sensor* strapped to a cows hind leg.

The *leg sensor* switches between the two states at an angle of $45° \pm 10°$. The observations are event sampled, i.e. each time the tag-angle passes the $45° \pm 10°$ limit an observation containing the time of the observation and the state value is sent to a central server, using Bluetooth wireless technology. Figure 2.4 shows a picture of a *leg sensor*.

Recordings from the *leg sensor* were available for a limited number of cows during the project period. As the system was under development during the project period long periods of missing data occur. Short period of missing data also frequently occur.

2.3   Feeding

Observations of the cows feeding behaviour were recorded by a number of special feeding boxes, produced by Insentec RIC system (Insentec, Marknesse, The Netherlands). The feeding boxes identify each cow that puts its head into a feeding box and register time for arrival and departure as well as consumed weight for each visit. Figure 2.5 shows a picture of a feeding box.

The recordings of the feeding behaviour were available for all cows when they were placed in an area with access to a milking robot. The recordings of feeding behaviour were available throughout the whole project period.

Figure 2.5: Feeding boxes. The blue boxes on the picture are the feeding boxes.

2.4   Data from automatic milking system

The automatic milking system (DeLaval, Tumba, Sweden), which is also referred to as a milking robot, identifies each cow entering and registers time for arrival and departure as well as amount of milk and a vast number of other parameters related to the milking, that were not utilised in this study. Figure 2.6 shows a picture of an automatic milking system.

The recordings of the milking data were available throughout the whole project period.

Figure 2.6: An automatic milking system.

2.5 IceTag3D® data

The IceTag3D® data consist of measurements of step counts and lying/standing behaviour recorded by the commercially available activity sensor IceTag3D®. The sensor is attached to the cow's leg and assesses the cow's activity in terms of the parameters *lying*, *standing*, *motion index* and *step count* using 3D-accelerometer technology. The sample period of the IceTag3D® is configurable and is for this project chosen as one minute. The first three parameters are the percentage of the sample period spent in each of the three states. The fourth parameter, the *step count*, is the number of steps in each sample period.

The parameters *lying* and *step count* are used for assessing lying behaviour and activity. The parameter *lying* was discretised into a binary variable based on previous studies (Munksgaard et al. [2006]),

$$y_m = \begin{cases} 0 \text{ if } lying_m \geq 50, \\ 1 \text{ if } lying_m < 50. \end{cases} \tag{2.1}$$

Thereby $y_m = 1$ means that the cow was standing, i.e. the leg was in a vertical position.

IceTag3D® recordings, that were observed from Sept-2008 to Apr-2009, were available for a total of 88 cows over periods of varying time length and with a varying number of *measuring sequences*. A measuring sequence is the time period in which an IceTag3D® has been continuously attached to a cow's leg. Transfer of data from the IceTag3D® to a computer was done by manually holding a data reader close to the IceTag3D®, thus enabling wireless data transfer.

This is required with 60 days intervals due to device storage limits. In some cases sensors were removed and changed with another tag. Towards the end of the study period all tags were removed and the data were transferred afterwards.

2.6 Manual oestrus observations

At the DCRC the cows are inspected twice daily for visual signs of oestrus. The inspector marks whether there are signs of:

1. Cows being mounted by other cows.

2. Cows mounting other cows.

3. Oestrus behaviour (friendly with other cows, hyperactive, licking or vocalizing).

4. Mucus coming out of the genitals.

5. Red and swollen vulva.

The staff uses a combination of the records from the visual inspections and the activity measurements from the ALPRO® activity tags to decide whether a cow should be inseminated or not.

2.7 Lameness scoring

The lameness scoring was performed by specially trained personnel at the Danish Cattle Research Centre, with around 2 weeks interval. The scoring is done by visually inspecting each cow for signs of lameness. The cow gets a "score" that describes the cow's physical condition with respect to lameness. The lameness scoring system is described in Thomsen et al. [2008] and an abridged description of the system is showed in Table 2.1.

It can be seen in Table 2.1 that having a lameness score ≤ 2 means that the cow is considered not to be affected by lameness while having lameness score > 2 means that the cow is considered to be suffering from lameness.

The lameness score 3 for mild lameness is in the lameness investigations often treated as a state of unknown lameness state as behaviour associated with lame-

Table 2.1: Lameness scoring system. An abridged version of that of Thomsen et al. [2008].

Score	Term	Brief description
1	Normal	The cow walks normally. No signs of lameness.
2	Uneven gait	The cow walks (almost) normally. No evident signs of lameness.
3	Mild lameness	Some signs of lameness. In most cases, an observer is not able to tell which leg is affected.
4	Lameness	Obviously lame on 1 or more legs. In most cases, an observer is able to tell which leg is affected.
5	Severe lameness	Obviously lame on 1 or more legs. Cow is unwilling to bear weight on the affected leg.

ness score 3 appears in many cases closer to that of the normal case than that of the lame case (see e.g. Figure 3.12 and Paper E).

The records of the lameness scoring are available from the years 2007 and 2008.

CHAPTER 3

Detection of oestrus and lameness

This chapter describes the development of algorithms for detecting oestrus and lameness in dairy cows.

During the development of methods for detecting oestrus and lameness the available recorded observations that are described in Chapter 2 were utilised for the detection. The solutions are therefore influenced by the available sets of recorded observations.

Classifying different behavioural scenarios from recordings of behaviour for detecting oestrus and lameness is a challenging task. When designing an oestrus detector one needs to bare in mind that the behaviours are not only varying on account of the oestrus or disease that is to be detected. There is also a natural difference in the behaviour between cows and there is a variation in behaviour over time. Among factors that are potentially affecting the behaviour are the cow's age, its lactation status, type of feeding material, whether it is pregnant, its health, the cow's individual behavioural responses (personality), the cow's placement in the herd hierarchy, and last but not least, the time of day, i.e. whether it is night or day.

The task is to identify which parameters or traits of observed behaviours differ between the two different scenarios, in oestrus/not in oestrus on one hand, and lame/not lame on the other. That difference is then utilised to distinguish

between the behavioural scenarios. The difference should be as distinct as possible. In order to retain the difference in observations between the two scenarios it can be beneficiary to undertake preprocessing of data, such as filtering or aggregation. Depending on the signature of the difference in the preprocessed data a detection method is chosen.

The detection methods, that are described in this thesis, are based on statistical change detection and model based diagnosis.

Statistical change detection is based on identifying statistical properties of a signal during normal and deviant behaviour. The task is then to detect changes in the probability distribution of the signal that is being analysed.

Model based diagnosis deals with defining a model of a system containing system components and connections between the components (Mozetic [1991]). The task is to compare observations of the system modelled with that of the model. If the two deviate from each other a deviant behaviour is considered detected. The model can describe a nominal behaviour as well as the deviant behaviour that is supposed to be detected.

The following sections describe the approaches used for the oestrus and lameness detection.

In the descriptions of the oestrus detection the notation *normal state* is used for the periods when the cow is not in oestrus and correspondingly *oestrus state* is used for periods where the cow is in oestrus.

Similarly for the lameness detection the notation *lame state* is used for the periods when the cow is suffering from lameness and *normal state* for the periods where the cow is not suffering from lameness.

The two subjects of detection, i.e. oestrus and lameness are treated separately. A cow that is assumed to be in normal state when detecting oestrus can easily be suffering from lameness. In the same way a cow, which is assumed to be in normal state when detecting lameness can be in oestrus.

3.1 Oestrus detection

3.1.1 Detection using activity

It is described in Section 1.6.1 how the activity is a widely used parameter for oestrus detection. The cow is expected to be generally more active when in oestrus and some signs of oestrus that are described in Section 1.3 such as mounting other cows in the herd can also result in an increased activity. The first approach therefore comprises an automatic oestrus detection using observations of the activity. This is described in Paper A.

Paper A comprises statistical change detection for the detection of oestrus. The data used for the study are the ALPRO® that are described in Section 2.1. An example of the activity signal of a cow that was in oestrus during the study period is shown in Figure 3.1. Figure 3.1 shows the raw activity index of a cow that was in oestrus nine times during a period of 6 months.

In Figure 3.1 it appears that the activity in a short period around oestrus state is considerably higher than during periods of normal state. What is also to be noticed is that the activity during different oestrus cases is varying considerably in amplitude between the individual cases. This is apparent when comparing, for example, the oestrus at 1.5 (May 1st 2006), two minor ticks on the x-axes after 29.4, to the one at 1.9 (September 1st 2006), two minor ticks after 30.8.

As mentioned in the description above there is a natural variation in the activity signal under normal conditions as well as under oestrus, which is also shown in Figure 3.1 where the oestrus cases are very different in amplitude. There is therefore a need to let the method depend on characteristics of the individual cow. The earlier mentioned factors that influence the activity level of each cow indicate that the activity behaviour is that different between cows that the use of pooled behaviour seems not feasible in order to obtain good results.

Cows preferably rest during night and are more active during the day. Diurnal variations in the activity are therefore to be expected. These diurnal variations in the signal should be removed as it is the increased activity that is associated with the oestrus that is to be detected rather than an increased activity on account of a diurnal variation. The risk is that for a cow that has a large diurnal variation in the activity, and a less distinct oestrus profile, the effects of the activity increase due to oestrus would partly vanish due to the diurnal variation. The diurnal variations are therefore modelled and the estimated level of the diurnal variation at each hour of the day is subtracted from the raw signal.
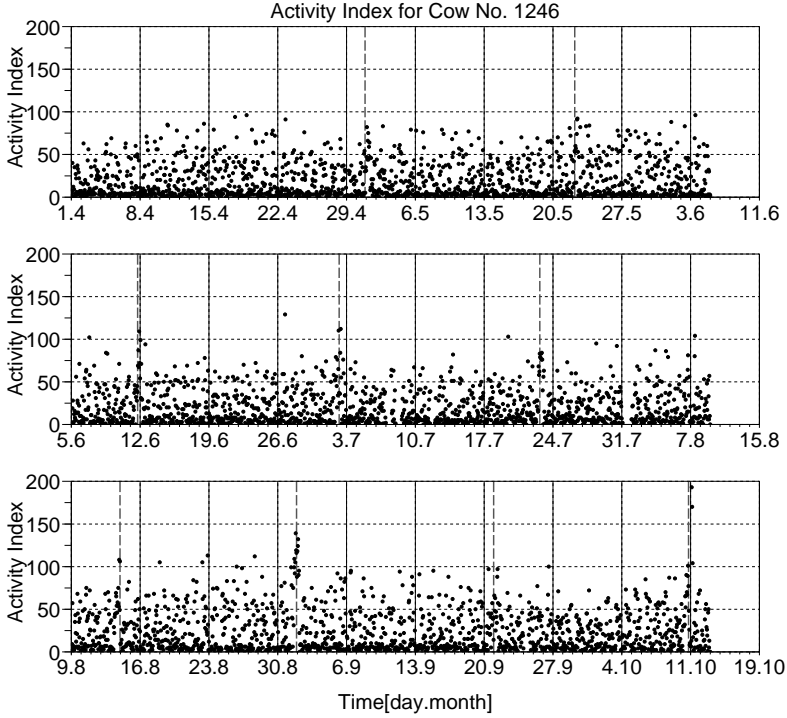
Figure 3.1: Activity index for a cow that was 9 times in oestrus during a period of 6 months in the year 2006. The oestrus cases are marked with dashed vertical lines.

The diurnal variations are modelled as a linear model where the diurnal profile is comprised of trigonometric functions of the frequencies in the diurnal variation. Denoting the activity y and the frequencies in the diurnal variations as $\omega_1 \ldots \omega_m$ the model becomes

$$
\begin{aligned}
y(k) \quad = \quad & \mu + A_1 \cos(\omega_1 k) + B_1 \sin(\omega_1 k) + \ldots \\
& + A_m \cos(\omega_m k) + B_m \sin(\omega_m k) + \varepsilon(k)
\end{aligned}
\tag{3.1}
$$

where k is the sample number, μ is the mean activity and ε is the residual.

The model estimation is done using a recursive least squares algorithm. Using a recursive algorithm ensures that slow changes in behaviour and differences between cows are counted for.

The frequencies of the diurnal variations $(\omega_1 \ldots \omega_m)$ are identified from the power spectrum of the activity and thereby identifying the frequencies in the activity signal. A power spectrum of a cows activity is shown in Figure 3.2.
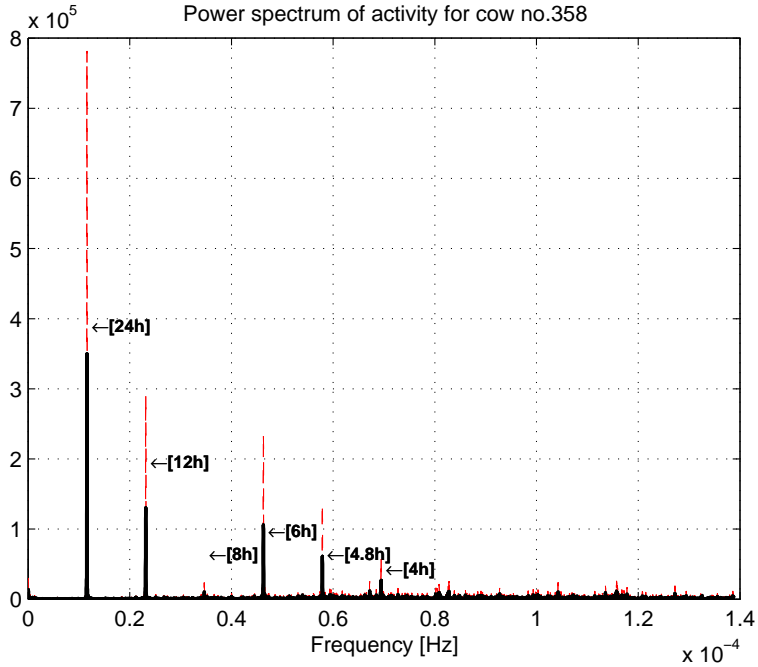
Figure 3.2: Power spectrum of a cows activity.

The frequencies that are used in the model are corresponding to periods of 24, 12, 8, 6, 4.8 and 4 hours.

The compensation of the diurnal variations and the generation of the residual is described in more details in Paper A, Section A.3.1.1.

The resulting signal after subtracting the diurnal variation is the residual with a mean value equal to zero.

The properties of the resulting residual are described by a Rayleigh distribution that is shifted "downwards" to have zero mean. Assuming a Rayleigh distribution is in correspondence with the fact that a distance measure $v = \sqrt{v_1^2 + v_2^2}$ is Rayleigh distributed if the v_1 and v_2 components are normally distributed ([Kay, 1998, pp. 30]). If considering the activity index to be a pedometer count, the activity index can approximate a distance measure.

Oestrus is then detected by testing when the mean value of the residual is different from 0.

The method used for detecting when the mean value changes is a generalized likelihood ratio (GLR) for detecting a change in mean value (see e.g. Basseville and Nikiforov [1993] and Gustafsson [2000]).

The normal behaviour is assumed to be described by the shifted Rayleigh distribution and the oestrus behaviour by a normal distribution. Assuming a normal distribution for the oestrus behaviour is done for reasons of practicality as the normal distribution is valid for all $x \in \mathbb{R}$. A more detailed reasoning for this choise is given in Paper A, Section A.3.1.2.

When testing the performance of the detection algorithm described in Paper A the results showed that 36 of the 42 oestrus cases were detected while generating 6 false alarms, which resulted in a sensitivity of 85.7%, specificity of 99.7% and an error ratio of 14.3%. The results are good compared to earlier results. An uncertainty in the analysis is, however, the relatively small number of oestrus cases included in the verification and the fact that the detection threshold was adjusted manually for each cow.

The results of Paper A were improved with respect to the number of false alarms, in Zarchi et al. [2009].

In Section 1.3 it is described how the oestrus has a cycle of 18-23 days from the first post-partum oestrus until the cow is pregnant. For reducing the probability of false alarms the period between two oestrus cases is utilised in a fuzzy logic classificator of the oestrus alarms. This was addressed in Zarchi et al. [2009].

Similar approaches have earlier been published in e.g. Mol and Woldt [2001] and Firk et al. [2003a]. The results in Zarchi et al. [2009] considerably improved the results of Paper A with respect to the number of false positives.

A test of the algorithm in Zarchi et al. [2009] showed that the number of false alarms were reduced from 6 down to 1 while only reducing the number of successful detections by 1 detection. The method showed to be advantageous but the same drawbacks as before with relatively few oestrus cases and manual setting of the individual detection threshold still apply.

As shown in Section 1.6.1 the use of activity as a measure for indicating oestrus behaviour has been thoroughly tested and documented over the years. In order to improve the detection performance the focus was therefore pointed towards lying behaviour, which had not been investigated with respect to the use in oestrus detection as extensively as the activity. This is described in the next section.

3.1.2 Detection using lying behaviour

According to Livshin et al. [2005], decreased lying time is an expected change in behaviour during oestrus. Observations of lying behaviour are therefore relevant for an investigation with respect to the applicability for an oestrus detection. As described in Section 2.2 the lying behaviour is observed by estimating two discrete states namely lying and standing. The first approach therefore comprises discrete event models, i.e. automata as is described in Paper B.

Automata are a class of models suitable for describing discrete-event systems. Various versions of automata are described in the literature, which includes e.g. standard automata Cassandras and Lafortune [2008], input/output automata (I/O automata) Lynch [1988], learning automata Poznyak and Najim [1997]. The version of automata applied in this study is the I/O automata.

In general the automaton describes a system's state and takes into consideration events that affect or are affected by the system.

Modelling a system using I/O automata can be done using deterministic automata, non-deterministic automata, stochastic automata or even timed automata (timed automata are addressed in e.g. Alur and Dill [1994] and Supavatanakul [2004]). The methods for the usage of the deterministic automata, the non-deterministic automata and the stochastic automata are well established and are described in e.g. Lunze and Schröder [2001], Schröder [2003] and Blanke et al. [2006]. Descriptions of the deterministic automata, the non-deterministic automata and the stochastic automata applied to the present problem can be found in Jónsson [2010].

For designing an automaton, data are considered. As mentioned above the data consist of observations of a discrete signal of a two value set, $\{lying, standing\}$. An intuitive choise for the model is therefore a two state model, with states standing and lying.

When using a two state model describing the states $\{lying, standing\}$, it is clear that an oestrus can not be detected by solely looking at which of the states the cow is in at each point in time. There has to be an additional signal included. An intuitive way of looking at it would be to consider the time spent in each state. An example of the time spent in each of the states lying and standing is shown in Figure 3.3.

When visually comparing plots of raw data during periods of oestrus state with periods of normal state, in Figure 3.3, it becomes clear that a time limit as a classification threshold, as in e.g. timed automata (Alur and Dill [1994]), is not
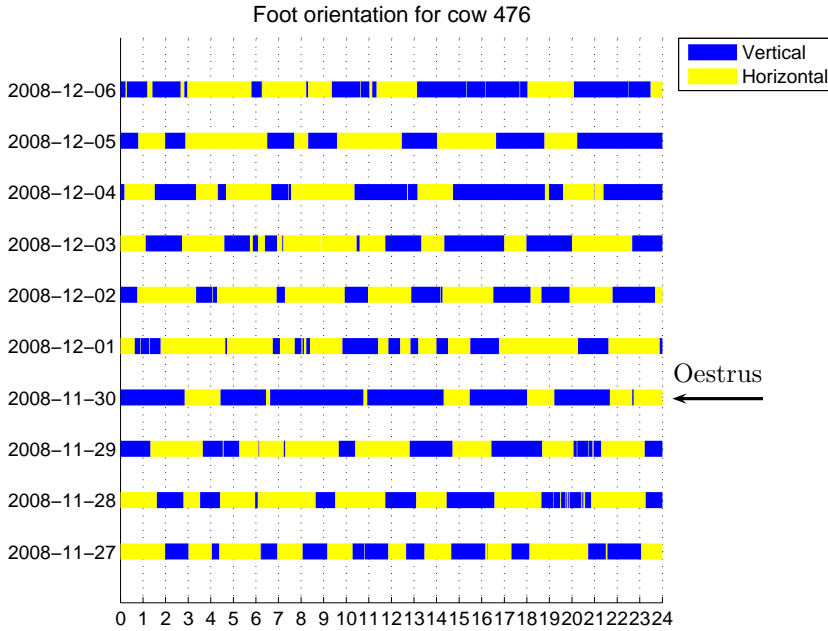
Figure 3.3: An example of the lying behaviour of a cow in the days around
an oestrus case. Each line in the plot corresponds to 24 *hours* of
lying behaviour from $[0, 24[$ *hours*. The lying periods are shown
in yellow and the standing periods in blue. An oestrus case is
indicated on November 30 year 2008.

suitable, as the longest standing period does not necessarily occur at oestrus.
The observed sojourn time spent in each state is stochastic. A suitable automata
model is therefore the stochastic automaton describing the probability of moving
from one state to another, i.e. going from lying to standing or the opposite. The
probability is to depend on how long the cow has been lying or standing during
the preceding period.

For this purpose a novel measure, the *lying-balance*, is suggested. The lying-
balance is meant as an indication of the internal motivational state of the cow
with respect to whether it wants to be lying or standing. The lying-balance
should thus function as an indication of how motivated the cow is for either
lying down or standing up.

The lying-balance is modelled with exponential functions. The idea behind using

(a) Lying   (b) Standing
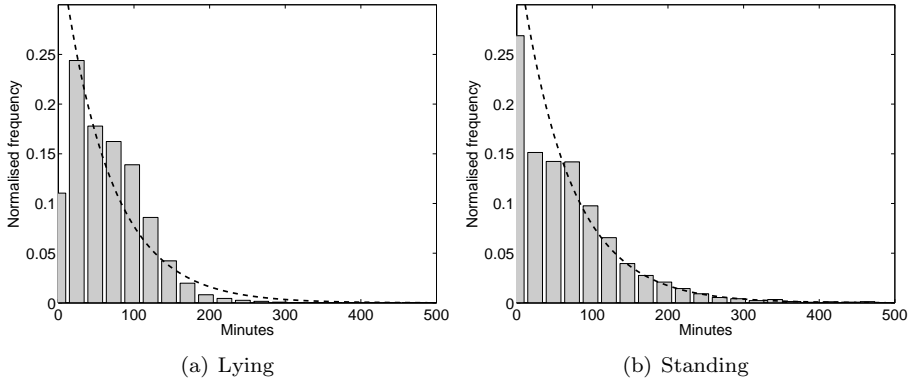
Figure 3.4: Histograms of pooled sojourn time in the states lying and stand-
ing for 18 cows over a period of 4 weeks. Probability distribu-
tion functions of fitted exponential distributions are plotted with
dashed lines.

exponential functions is built on an assumption that a certain period lying down
has greater influence on the motivation if the cow has not been lying much in
the preceding period than if it is fully rested. This is further supported by the
fact that the duration of the observed lying and standing periods appear to be
exponentially distributed. This is shown in Figure 3.4.

The lying balance is described in details in Section D.2.5.1, Paper D.

Figure 3.5 shows an example of the lying-balance. The figure shows the calcu-
lated lying-balance for one cow during 2 days of normal behaviour and 2 days
where oestrus occurs. In Figure 3.5 it is apparent how the lying-balance is lower
during oestrus than during normal behaviour.

For being able to use the lying-balance, which is a continious variable, in the
automata, the lying-balance is quantised into a set of discrete values. The
quantised lying-balance is modelled as the output of the automaton.

For detecting whether the cow is in oestrus or not the model is diagnosed where
the consistency between the automaton and the actual behaviour is checked
(see e.g. pp. 414 in Blanke et al. [2006]). Lack of consistency implies that
the observed behaviour is not described by the automaton. By modelling a
specific behaviour to be detected and checking the consistency between the
model describing the deviant behaviour and the actual behaviour a specific
deviant behaviour can be detected. If the observed behaviour is not consistent

(a) Normal behaviour

(b) Oestrus behaviour
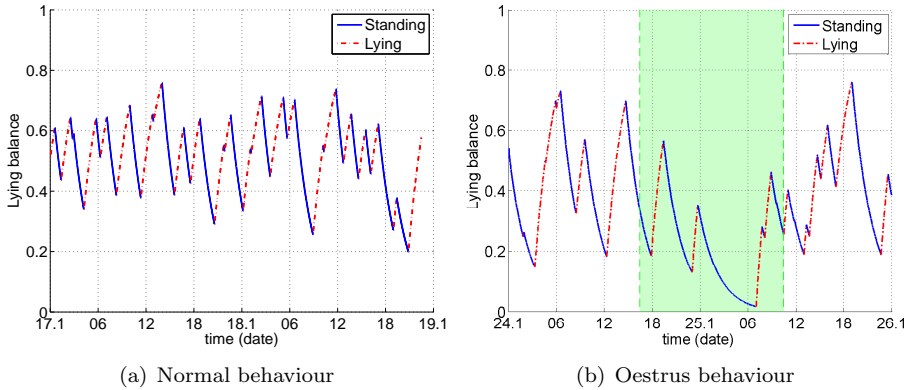
Figure 3.5: An example of the lying-balance. The shaded area shows the 18 hour period of the assumed oestrus (see (7) in Section D.2.4)

with the normal case and, at the same time, there exists consistency with the model of the specific deviant behaviour, the specific behaviour is isolated.

Each of the behavioural scenarios that should be detected is modelled with an automaton. The automata for each of the different behavioural scenarios are coupled using a fault model. The lying behaviour during oestrus and normal states is thus modelled by stochastic automata – one model describing the normal state and another model for describing the oestrus state. The probability of moving between the two states normal and oestrus is then described by the fault model (see e.g. pp. 21-22 in Jónsson [2010]).

The algorithm in Paper B was applied on the observed lying behaviour of one cow. Automata models of the normal and oestrus behaviour were trained by observing the number of transitions at different values of lying–balance at normal and oestrus states respectively. The transition probability of moving between the states *lying* and *standing* then depends on the number of observed transitions at the different levels of lying–balance for the normal and oestrus case, respectively. The oestrus case was detected without a false alarm. This gave an indication that the algorithm could be used for detecting oestrus.

Further development and testing of the algorithm showed that the lying behaviour as a sole trait for detecting oestrus was not suitable. Therefore further studies aimed at investigating whether the lying behaviour would improve the oestrus detection by combining it with the activity. This is addressed in the following section (Section 3.1.3).

3.1.3   Detection from combined activity and lying behaviour

To improve the oestrus detection, the activity and lying behaviour are combined in one detection algorithm. Although the activity and lying behaviour to a certain extent express the same information, i.e. on when the cow is resting/being active, the lying behaviour produces the extra information on whether the cow is spending more time standing during oestrus than during non oestrus behaviour. Although the cow perhaps stands more during oestrus it does not necessarily result in higher activity if the cow is standing still. Combining the two signals in one detector should therefore potentially improve the oestrus detection.

Two different methods for combining observations of activity and lying behaviour in a detector are tested. In the first version of the combined detector, both activity and lying behaviour are modelled with discrete event models, i.e. automata. In the second version the two traits are combined in a detector using statistical change detection.

3.1.3.1   Combining activity and lying behaviour using automata theory

Oestrus detection combining activity and lying behaviour using automata is the subject of Paper C. For the development of the automata models for the oestrus detection using both activity and lying behaviour, the ALPRO® activity data and the *leg sensor* lying behavioural data are used (see Section 2.1 and 2.2).

As mentioned earlier, in Section 1.3, when a cow is in oestrus, the activity is expected to increase (Kiddy [1977], Schlünsen et al. [1987]). If considering the activity behaviour in a qualitative manner one could claim that if quantising the activity index into several levels, the higher levels should help distinguishing between the normal and the oestrus state as these would be observed more frequently during oestrus behaviour than during normal behaviour. For modelling the activity with a stochastic automaton the quantised activity levels represent the states of the activity model. The activity state is assumed to be measurable. Assuming a measurable state and not using any input, categorises this automaton as an autonomous stochastic automaton with measurable states.

The activity index is quantised into a set of 4 discrete values, which in this case is also the number of states in the model. The 4 states qualitatively divide the activity into levels that indicate different amplitudes of the activity. The higher levels should be less frequently observed during normal behaviour while they should be more frequently observed during oestrus. This difference is described

by modelling the normal and the oestrus behaviour in two different automata models, one describing the normal behaviour and one describing the oestrus behaviour. As it is known that the short term amplitude of the cows activity can be just as large during normal behaviour as during oestrus behaviour all 4 states can possibly occur in both models. The difference between the two lies in the transition probability. In the normal model the probability of moving towards state 4 (the highest activity) will be smaller than in the oestrus model. Staying in state 1 has however larger probability in the normal model than in the oestrus model.

To find out whether the cow is in oestrus or not, the automata model is diagnosed.

The lying behaviour is modelled separately from the activity with a two state automaton as described above in Section 3.1.2.

Each of the two detectors of activity and lying behaviour, respectively, return a boolean signal $\{true, false\}$ on the hypothesis that the cow is in oestrus. The two detectors are combined in one detector by a simple logic gate. As neither the activity detector nor the lying-balance detector are particularly sensitive, the result is that if either detector detects a possible oestrus, an alarm is issued. Hence the logic gate is an *or* gate. The algorithm was tested on activity and lying behaviour data from 10 oestrus cases from 10 cows with subsequent confirmed pregnancies. The detection test showed a sensitivity of 100% and a specificity of 99%. Results that indeed are very good. However, the results can only be considered as promising due to the small number of oestrus cases included in the validation test. A detailed description of the test method is included in Paper C.

3.1.3.2 Combining activity and lying behaviour using statistical change detection

The above described automata method for implementing an oestrus detection, combining activity and lying behaviour, has the limitations that no other changes in the behaviour other than the increase in activity and increased time spent lying are taken into account. Allowing also the expected duration of oestrus and the length of the oestrus cyclus to be taken into account could potentially improve the oestrus detection. This was done by combining the two signals using an algorithm based on statistical change detection. This is described in Paper D.

For the development of the statistical change detection for the activity and

(a) Normal behaviour   (b) Oestrus behaviour
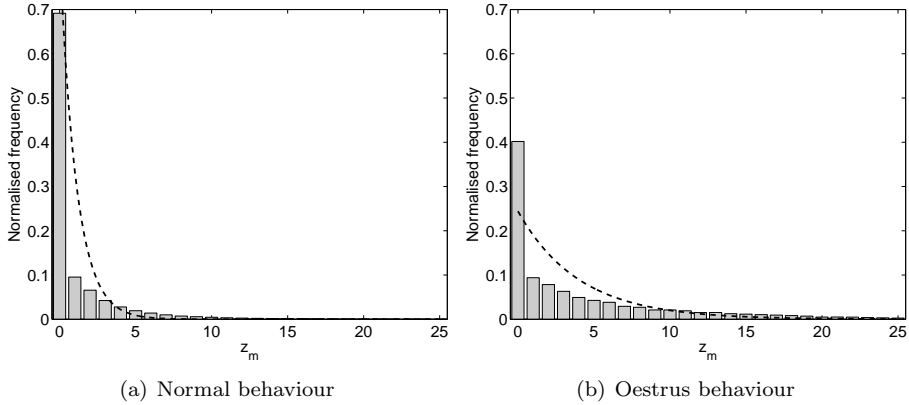
Figure 3.6: Histograms of number of steps per minute, z_m, for the *study cows* under normal behaviour and oestrus behaviour respectively. Probability distribution functions of fitted exponential distributions are plotted with dashed lines.

lying behaviour combined, the IceTag3D® data are used (see Section 2.5). As described in Section 2.5, the IceTag3D® returns signals describing the cows' activity in terms of the parameters *lying*, *standing*, *motion index* and *step count*. Of the signals, that the IceTag3D® estimates, the detector uses the number of steps per minute (step count) and the time spent lying. The time spent lying is converted into the lying-balance that was described in Section 3.1.2.

In search for a suitable detection algorithm, the data were investigated by plotting histograms of the data. Figure 3.6 and Figure 3.7 show histograms of the pooled activity and lying-balance during normal and oestrus states, respectively. The two figures, especially for the lying-balance (Figure 3.7), indicate that the detection could be done using statistical change detection as the statistical properties of the normal and the oestrus behaviour appear to be somewhat different.

The step count, shown in Figure 3.6, is fitted with exponential distributions under both normal and oestrus states. As it is described in Paper D the maximum likelihood estimates (MLE) of mean value and standard deviation are not the same in the two cases, normal and oestrus. Nevertheless, the exponential distribution was selected for the step count detection, for reasons of practicality, and the fact that selecting the exponential distribution does, that the algorithm reacts to changes in both mean value and standard deviation, both of which increase during oestrus.
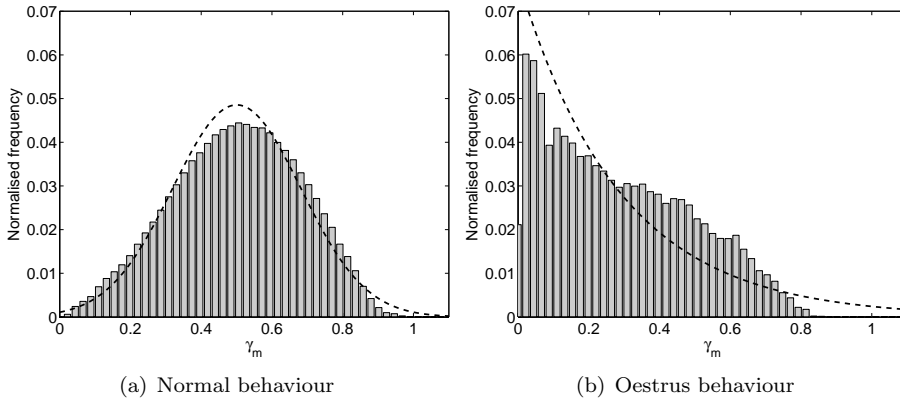
(a) Normal behaviour   (b) Oestrus behaviour

Figure 3.7: Histograms of lying-balance, γ_m for the *study cows* under normal
behaviour and oestrus behaviour respectively. Probability distri-
bution functions of a normal distribution fitted to the normal data
and an exponential distribution fitted to the oestrus data are plot-
ted with dashed lines.

The distributions for the lying-balance during normal and oestrus behaviour,
shown in Figure 3.7, are fitted by normal and exponential probability density
functions, respectively.

The two signals, step count and lying-balance, are each utilised in a generalized
likelihood ratio detector (GLR) based on the above mentioned distributions.

A number of measures are undertaken to adapt the GLR detectors of the step
count and the lying balance, respectively, to the detection of oestrus in dairy
cows.

The detector will most likely perform better if the distribution parameters in the
GLRs are estimated on-line for the individual cow than if the parameters were
estimated off-line for the whole herd. The parameter estimation is therefore
done using exponentially weighted moving average (EWMA) (Hunter [1986])
and exponentially weighted moving variance (EWMV) estimation (MacGregor
[1993]). For the estimation of both mean and variance, the memory factor
that controls the weighting between the influence of the new observation and
earlier estimated values, is tuned so that the expected length of the oestrus cycle
is taken into account. That way, the estimate converges towards the normal
behaviour between two consecutive oestrus cases.

Also to increase the performance of the algorithm, it was restricted to find

changes in the behaviour that were lasting for as long as an oestrus is expected to last but not longer. The detectors were also restricted to only detect changes in the correct direction, i.e. an increased step count and reduced lying-balance. This is described in Section D.2.3, Paper D.

The distributions of the two detection signals from the GLR on step count and lying-balance are not known. The two detection signals are characterised by low values and then some few extreme values, where the detection is initiated if exceeding a threshold. The variance of the detection signals is therefore increased and thereby the two signals should be correlated during oestrus. This leads to combining the two detection signals using exponentially weighted moving covariance. This is described in Section D.2.6, Paper D.

An adaptive detection threshold is based on the historical maximum values of the combined detection signal. Minimum and maximum threshold values, h_{min} and h_{max} are introduced. The selection of the length of the historical horizon is based on the expected period between two consecutive oestrus cases. This is described in Section D.2.6.1, Paper D.

Figure 3.8 shows a scatter plot of the step count detection signal with respect to that of the lying-balance. The figure also shows the minimum and maximum thresholds, h_{min} and h_{max}.

Figure 3.8 shows that the two decision functions are correlated during oestrus. The figure therefore supports the selection of the combination method in Eq. (18), in Section D.2.6, Paper D.

The detection algorithm was tested on 18 oestrus cases for 18 cows with subsequent confirmed pregnancies. The detection test resulted in a sensitivity of 88.9%, specificity of 99.8% and an error ratio of 5.9%, very good results, especially when looking at the low error ratio.

3.2   Lameness detection

As described in Section 1.4, lameness is expected to reduce the cows' motivation to move around and being active. Lameness can therefore change the cows' behaviour with respect to many behavioural traits such as activity (O'Callaghan et al. [2003], Mazrier et al. [2006]), feeding behaviour (Bach et al. [2007], Gonzalez et al. [2008]) and milking behaviour (Borderas et al. [2008]).

The changes in activity, feeding behaviour, and milking behaviour are investi-
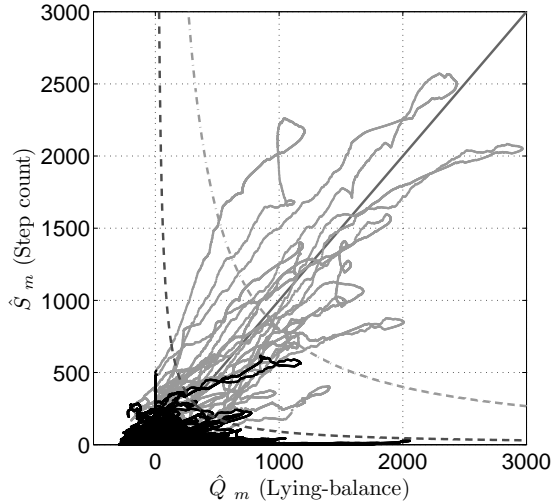
Figure 3.8: Scatter plot of the detection signals from the GLR on step count
and lying-balance respectively. The value of the decision functions
during oestrus is shown in grey dots and during periods of normal
behaviour in black dots. The thresholds h_{min} and h_{max} are shown
as dashed and dash-dotted lines.

gated in two different studies. The first one investigates the suitability of using
automata theory for detecting lameness in dairy cows from recorded observa-
tions of activity. This is described in Section 3.2.1. The latter study investigates
the suitability of using activity, feeding behaviour and milking behaviour in a
lameness detector based on discriminant analysis. This is described in Section
3.2.2.

3.2.1   Lameness detection using automata models of activity

The possibility of using discrete–event models that describe the cows' behaviour
for detecting lameness dairy cows was investigated in Jónsson [2010].

The focus was on investigating whether model based diagnosis would be suitable
for the detection of lameness. The model used was the stochastic automaton.

The discrete–event model, in this case the stochastic automaton, should describe
the cows' behaviour in terms of parameters which change in the presence of

lameness. The parameters analysed in this study are observations of the cows' activity. As the main symptoms of lameness involve feet illnesses it is intuitive to associate these with changes in activity. Changes in activity in connection with lameness have been pointed out in e.g. O'Callaghan et al. [2003] and Mazrier et al. [2006] and the detection of lameness using observations of activity has been carried out in Mazrier et al. [2006]. Although the authors of Mazrier et al. [2006] did not succeed in developing a convincing lameness detector solely based on activity it is still a relevant parameter for further studies of lameness detection. The detection method used in Mazrier et al. [2006] was quite plain and results should be possible to improve.

For the selection of model and the definition of states, inputs and outputs, it should be kept in mind that the model is supposed to describe the cows' activity and that the diagnosis task is to detect changes in the activity behaviour due to feet illnesses (lameness). The modelling aim is therefore to construct a model that retains differences in activity between nominal and lame behaviour.

No data preprocessing other than a quantisation was performed. If a detection is possible using observations of raw data observations this is likely to be faster than a detection performed on observations that have been pre-processed/filtered using e.g. an aggregation or a running mean.

Three ways of modelling the cows activity with an automaton were tested in Jónsson [2010].

As the cow is a living being, an individual if you will, that can move freely within some boundaries in a loose housing system, it is a natural assumption to consider the cow as an autonomous system with respect to its activity behaviour. This is what is comprised in the first modelling approach, where the cow is modelled as an autonomous system with raw measurements of activity index as measurement output.

In the first approach, the states describe the activity during the last hour, i.e. a qualitative measure of the activity index described in Section 2.1. This is realised by the autonomous stochastic automaton with coinciding states and outputs.

It is well known that the cows' activity follows some sort of a diurnal rhythm (see e.g. Jónsson et al. [2008], Paper A). One could therefore assume that it is justifiable to consider the time of day as some kind of an input or disturbance controlling the systems activity. This is what is done in the second approach by adding quantised time of day as an input to the stochastic automaton. In this case the system is as before considered to have raw activity index as measurement output. The modelling aim of the second approach is therefore to model

the cow's activity as a function of the time of day.

In the third approach the modelling aim is to model a general activity level of the autonomous cow. The model should describe whether the cow is experiencing an active period rather than describing a more instantaneous activity as in the two earlier approaches. In this approach the state is therefore defined as a measure of the general activity state of the cow in terms of a some sort of a mean value. Hence if the activity observations are generally high the activity state should also be high, but although a single low activity observation appears it doesn't necessarily mean that the state should change over to a low activity state, thus the activity state is a kind of a moving average of the activity observations. The output on the other hand expresses the direct measurement of the current activity index which means that the activity state is not directly observable.

The changes in activity in connection with lameness are investigated using the ALPRO® activity data. For assessing the lameness state, the lameness observations that are described in Section 2.7 are used. As described in Section 2.7 the lameness scoring is performed with a 14 days interval, i.e. the lameness state of the cow in the 14 days interval between 2 consecutive observations is in fact unknown. The study described in Jónsson [2010] utilises the activity data of a cow that had a long period with only lameness scoring ≤ 2 and then later a period with 5 consecutive observations of lameness scores ≥ 4. As the cow had several consecutive observations of lameness scores ≥ 4 it seems fair to make the assumption that the cow had been suffering from lameness also in the periods between the lameness observations.

Investigations on the activity behaviour of the cow, that had 5 consecutive observations of lameness scores ≥ 4, show reduced activity in the period where the cow was observed to be lame. Further investigations showed that the difference was more apparent in the morning and in the evening than during other periods of the day (see Figure 3.9).

In all three approaches, the behaviour during normal state and lame state were modelled with stochastic automata and a fault model coupling the two automata. The fault model assumed very little probability of moving between the states, normal and lame respectively. For extracting the difference in behaviour between the normal and the lame case the activity was quantised into discrete sets as shown in Figure 3.9.

As mentioned above, for enhancing the difference, an input with the quantised time of day was added to the model in the second approach. This resulted in the quantisation in Figure 3.10.

The quantisation with respect to the time of day was aimed at placing limits

(a) Normal   (b) Lame
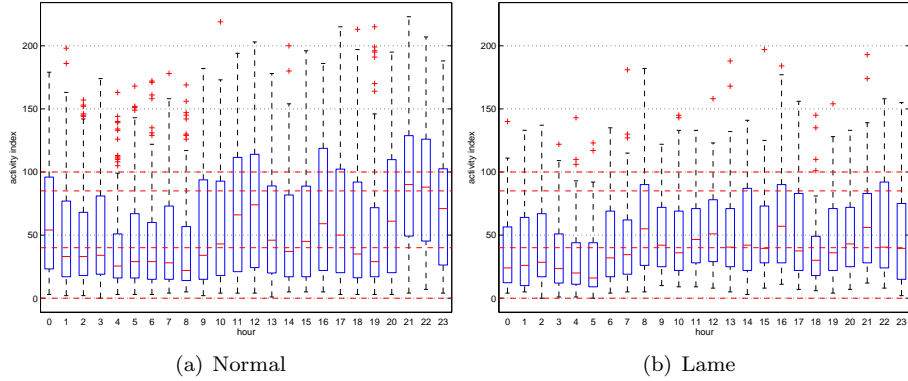
Figure 3.9: Quantisation of the activity level shown on box plots of the activity
for each hour in the day. The quantisation intervals are 1) $[0; 40[$,
2) $[40; 80[$, 3) $[80; 100[$, 4) $[100; 150[$. The quantisation intervals are
indicated with horizontal dash-dotted lines in red. The red line
inside each box shows the median. The upper and lower edges
of the box show the 75% and 25% quantiles, respectively. The
dashed lines show the 95% and 5% quantiles and the red dots are
outliers.

between two different values, i.e. two consecutive periods of the day, where the
behaviour changed, in either of the scenarios, normal or lame. Figure 3.10 shows
that there is a change on the right figure there is a change in median value from
before $05:30$ to the interval $5:30-11:30$. It is also evident that activity in
the nominal case is especially high compared to the faulty case in the interval
$18:30-24:00$.

In order to facilitate comparison of the diagnosis results of the three approaches,
a plot of the absolute difference, between the probability of the data measure-
ments belonging to the nominal behaviour, for each of the tree approaches, and a
"truth" reference, was drawn. The "truth" reference is ment to indicate whether
a measurement sample belongs to nominal behaviour or faulty behaviour. De-
noting the "truth" reference by q the truth reference is selected as

$$q(k) = \begin{cases} 1 & \text{if } k = 0 \ldots 3906 \\ 0 & \text{if } k = 3907 \ldots 5395 \end{cases} \tag{3.2}$$

where k is the sample number. Hence $q(k)$ is equal to one in the period be-
longing to the nominal behaviour and zero in the period belonging to the faulty
behaviour. The absolute difference between the probability of the data measure-
ments belonging to the nominal behaviour and the "truth" reference is therefore

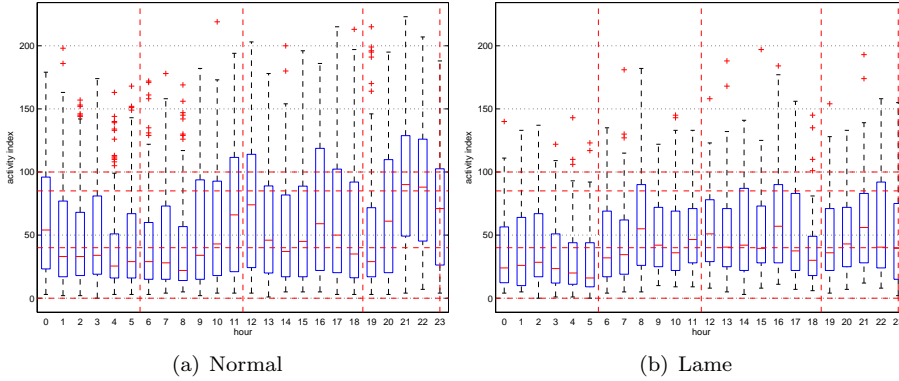(a) Normal   (b) Lame

Figure 3.10: Quantisation of the activity level and time of day shown on box
plots of the activity for each hour in the day. The quantisation
intervals for the activity are 1) $[0; 40[$, 2) $[40; 80[$, 3) $[80; 100[$,
4) $[100; 150[$ and are indicated with horizontal dash-dotted lines
in red. The quantisation intervals for the time of day are 1)
$[00 : 00; 05 : 30[$, 2) $[05 : 30; 11 : 30[$, 3) $[11 : 30; 18 : 30[$, 4)
$[18 : 30; 00 : 00[$ and are indicated with vertical dashed lines in
red. The red line inside each box shows the median. The upper
and lower edges of the box show the 75% and 25% quantiles,
respectively. The dashed lines show the 95% and 5% quantiles
and the red dots are outliers.

found as

$$\epsilon_f(k) = |q(k) - \text{Prob}(f(k) = 1|k)| \tag{3.3}$$

for each of the three approaches. $\epsilon_f(k_h)$ was calculated for the whole period for
each of the three approaches and is shown in Figure 3.11.

From Figure 3.11 it can bee seen that there is some difference between the three
approaches and that approach two and three are clearly performing better that
approach one.

3.2.2 Lameness detection using maximum likelihood classification

Despite promising efforts in Jónsson [2010] further investigations on the activ-
ity showed that too little difference was to be found in the activity behaviour
between the normal and the lame states for basing a lameness detector solely on
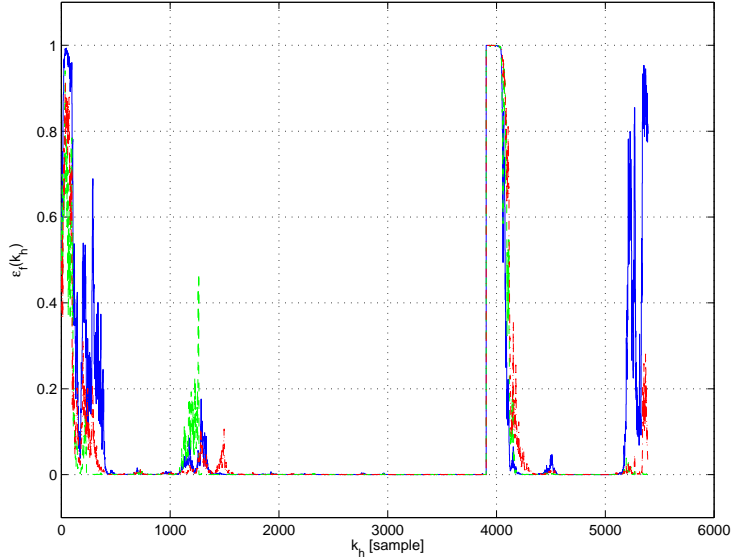
Figure 3.11: A plot of the diagnosis error $\epsilon_f(k_h)$ for the three modelling approaches. The blue line represents $\epsilon_f(k_h)$ for the diagnosis in the first approach, the green dashed line represents $\epsilon_f(k_h)$ for the diagnosis in the second approach and the red dash-dotted line represents $\epsilon_f(k_h)$ for the diagnosis in the third approach.

the activity trait. Therefore, in addition to the activity, other traits are further investigated in order to address their suitability for detecting lameness. This study is described in Paper E. The study included the traits 1) activity (Section 2.1); 2) feeding behaviour (Section 2.3) and 3) milking behaviour (Section 2.4). The lameness state is assessed using the lameness values that are described in Section 2.7.

As mentioned above the lameness state of the cow is unknown in the period between two consecutive lameness observations. Therefore in the study that is described in Paper E only the observations that are recorded on days where lameness observations are performed are used for assessing the behaviours during normal and lame states.

In order to get an indication of the difference in behaviour between the lameness states a plot of the 24–hour mean values for the behavioural traits analysed was plotted in Figure 3.12.

Figure 3.12 shows the estimated mean values and standard deviations of daily
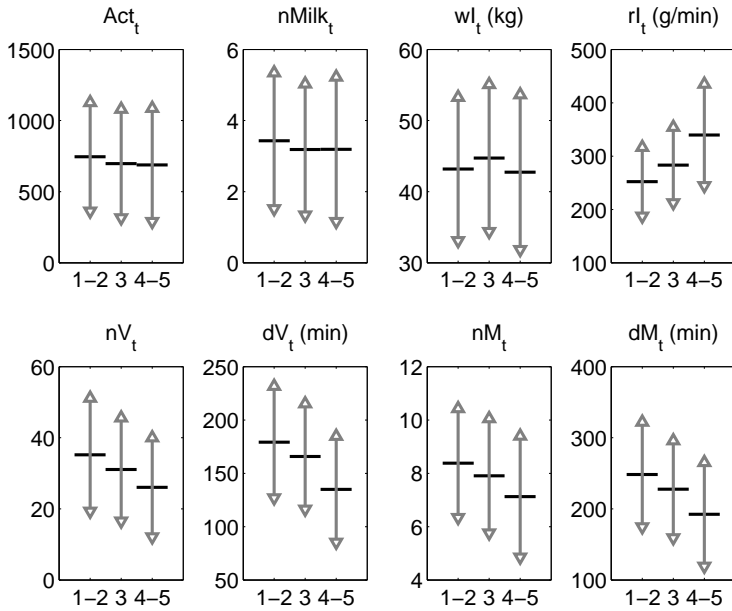
Figure 3.12: Estimated mean values and standard deviations of behavior and
feed intake versus lameness score. All values are summed over
24 h. Lameness scores are divided into 3 groups, 1) normal
state, $S_t \in \{1, 2\}$; 2) mild lameness, $S_t \in \{3\}$; 3) lame state,
$S_t \in \{4, 5\}$. The lameness scores are indicated on the x-axis.
The plotted variables are activity (Act_t), number of visits to the
milking robot ($nMilk_t$), feed intake (wI_t), feed intake rate(rI_t),
number of visits to the feeders or feed bins (nV_t), duration of vis-
its to the feeding bins (dV_t), number of meals (nM_t) and duration
of meals (dM_t).

values of the behavioural traits (aggregated over 24–hours), 1) activity Act_t; 2)
the number of visits to the feeders or feed bins nV_t; 3) the duration of visits
to the feeding bins dV_t; 4) the number of meals nM_t; 5) the duration of meals
dM_t; 6) the feed intake wI_t; 7) the feed intake rate rI_t and 8) the number of
visits to the milking robot $nMilk_t$.

Viewing Figure 3.12 it appears that noticable differences are to be found in the
intake rate, number of feeding visits and meals, and in the duration of feeding
visits and meals. It should be noticed though, that all changes are relatively
small seen with respect to the standard deviations. Figure 3.12 shows that all
the traits, except one, decrease when the cows are lame. The only trait that

(a)   (b)
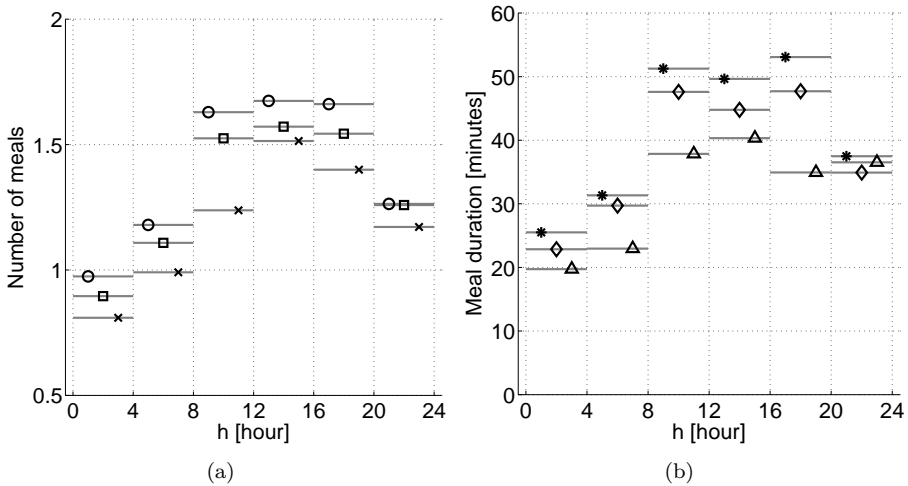
Figure 3.13: Estimated mean values of the aggregated number of meals and
the aggregated duration of meals during the day, split into 6
intervals. Plot (a) shows the estimated mean values for pooled
lameness scores $S_t \in \{1, 2\}$ with a *circle*, $S_t \in \{3\}$ with a *box*
and $S_t \in \{4, 5\}$ with a *cross*. Plot (b) shows the estimated mean
values of the duration of meals for $S_t \in \{1, 2\}$ with an *asterisk*,
$S_t \in \{3\}$ with a *diamond* and $S_t \in \{4, 5\}$ with a *triangle*. The
estimated standard deviation of the number of meals per day
when aggregating over 4 h was found as SD = 0.8. For the mean
of duration of meals the standard deviation was SD = $31min$.

increases is the intake rate, the intake rate increases as the daily duration of
meals is decreased while the daily intake is a lot less decreasing.

In the same way as for the activity in Section 3.1.1, some diurnal variations are
to be expected in the traits that are shown in Figure 3.12 apart from the intake
rate. The intake rate is not expected to change during the day.

With the purpose of revealing some differences in the behaviour depending on
which time of day it is, figures were plotted where aggregated behaviour was
split into several intervals over the day. Figure 3.13 shows the estimated mean
values of the number of meals and the duration of meals during the day, split
into 6 intervals.

From Figure 3.13 it appears that the difference in feeding behaviour is largest
in the morning and in the evening but less during night and afternoon. Viewing

Figure 3.13 also shows that splitting the daily behaviour into several periods enhances the difference there is between the normal and the lame states.

The classification of behaviour is done using a maximum likelihood classification algorithm. The algorithm operates with days, i.e. each days behaviour is classified as either normal or lame. Denoting t as the day, recorded observations in a feature vector $\mathbf{X}_t$ are classified. The number of periods that the daily behaviour is split into as well as the number of traits included, determine the length of $\mathbf{X}_t$. Thus if splitting the day into 3 intervals and using only number of meals, $\mathbf{M}_t$, in the given periods the feature vector $\mathbf{X}_t = \mathbf{M}_t$ becomes a vector of 3–elements. If classifying using $\mathbf{M}_t$ and duration of meals, $\mathbf{D}_t$, then $\mathbf{X}_t = \begin{bmatrix} \mathbf{M}_t & \mathbf{D}_t \end{bmatrix}$ becomes a 6–elements vector.

In the classificator the posterior probability that the sample $\mathbf{X}_{t-d}$ at time $t-d$ belongs to the group c_1 (normal), i.e., $P(c_1|\mathbf{X}_{t-d})$ is found as

$$P(c_1|\mathbf{X}_{t-d}) = \frac{p_1 f_1(\mathbf{X}_{t-d})}{p_1 f_1(\mathbf{X}_{t-d}) + p_2 f_2(\mathbf{X}_{t-d})} \tag{3.4}$$

where $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ are the estimated probability density functions (pdfs) of the normal and the lame behaviours respectively, and p_1, p_2 are the prior probabilities of c_1 and c_2, respectively. In this study the prior probabilities are selected as $p_1 = p_2 = 0.5$. For improving the probability of correct classification, more than one day are included in the classification. For this purpose the logarithm of the posterior probabilities are summed over d number of days prior to the day of the observation t. The sum thus becomes

$$Q_t(c_1|t-1) = \sum_{i=t-d}^{t-1} \log(P(c_1|\mathbf{X}_i)) \tag{3.5}$$

The classification selects the group with the largest sum Q_t.

The best results were gained when classifying between normal behaviour as $c_1 : S_t \in \{1, 2, 3\}$ and the oestrus behaviour as $c_2 : S_t \in \{4, 5\}$, i.e. grouping lameness scoring $S_t \in \{3\}$ as normal behaviour, using activity and aggregated number of meals split into 3 intervals during the day, the aggregated duration of meals split into 6 intervals during the day, the feed intake and the number of visits to the milking robot. The logarithm of the posterior probabilities was summed over 2 days including the day of the manual lameness observations. This resulted in a sensitivity of 75.5% and a specificity of 73.5%.

More detailed description of the results and method is given in Paper E.

Chapter 4

Conclusions and perspectives

4.1 Conclusions

During the course of the project, methods were developed for detecting oestrus and lameness in dairy cows using statistical change detection as well as model based diagnosis.

Algorithms for detecting oestrus in dairy cows were developed for 4 different types of input signals, 1) an hourly sampled activity index, measured at the cow's neck; 2) an event sampled binary signal indicating each time the cow either stands up or lies down; 3) the number of steps taken by a cow in a given time interval and 4) a binary signal indicating if a cow was mainly lying or not in a given time interval.

For the hourly sampled activity index signal diurnal rhythms of the normal behaviour were identified. Compensating for diurnal activity variations for individual animals and recursively estimating distribution parameters for the individual, statistical change detection theory was applied on oestrus detection.

In order to improve the performance of the oestrus detection algorithm activity and lying behaviour were combined in one detector based on statistical change detection. The algorithm employed the signals indicating the number of steps taken over each minute and the binary signal indicating if the cow was mainly

lying or not in a given time interval.

Specifically, the step counts were used in a detection algorithm which was designed to accommodate non Gaussian data. Furthermore, a lying balance was introduced as a biologically inspired quantity describing how much the cow has been lying during the preceding period. The input to this balance was the binary lying variable. A statistical change detection algorithm based on this balance was designed. Detection was investigated when combining the two statistical change detectors.

Both detection algorithms exploited knowledge of the expected intervals between oestruses and expected duration of oestrus and technicalities such as the known direction of change were utilised. A virtue of the algorithms is that they are based on on-line estimation of parameters for the individual animals. This is important from a practical point of view if an implementation of the algorithms in farm equipment is envisaged: There is no global set of parameters which are needed; instead the cow specific parameters are estimated on–line as data is observed.

The results of the combined detector showed clearly improved performance in comparison with only using the activity as the sole trait, enhancing the number of successful alerts and significantly reducing the number of false positives.

Model based methods were investigated with respect to the applicability of modelling the cows behaviour for detecting oestrus and lameness.

Qualitative modelling was used to model a cows' lying behaviour with the goal of detecting oestrus using the event sampled binary signal indicating each time the cow either stands up or lies down. Input to the model were the actual lying/standing state and the above mentioned lying balance. The cows' lying behaviour during normal and oestrus states were modelled using stochastic automata and the oestrus was detected diagnosing the automata model. Testing the algorithm on lying data for one cow indicated that detecting oestrus using observations of lying behaviour and modelling the behaviour with at stochastic automata was possible.

Further work on the model based methods led to combining the hourly sampled activity index and the event sampled observations of the lying behaviour using stochastic automata. The lying behaviour was modelled using the above described stochastic automata and another stochastic automata were derived for the activity behaviour during normal and oestrus states. The automata models were diagnosed for detecting oestrus and the binary alarms of the lying behaviour and activity automata were combined. Testing the algorithm showed good results with respect to the number of successful detections and the number

of false alarms but further tests on a larger dataset are needed to further verify the performance.

Lameness detection was utilised using linear discriminants on variables describing the cows activity, feeding behaviour and the number of milkings per day.

Realising an effective and reliable lameness detection showed to be a difficult task. However promising results on the lameness detection were obtained using only low-cost sensor equipment. The results were comparable to earlier results though reducing the number of traits in comparison with earlier publications. Varying results were obtained depending on the number of traits included in the analysis. Considering observations that are split into several intervals during the day proved advantageous as this to a certain degree compensates for the diurnal variations in the behaviour. The detection is at every time based on observations of the three preceding days, which gives a higher probability of detection and a reduced probability of initiating a false alarm.

4.2   Perspectives

Future perspectives for the work on oestrus and lameness detection, that is described in this thesis, involve mainly further verification of the results and tests with respect to practical usage.

Looking at the results of the oestrus detection, the results are very promising. Especially when combining measurements of activity with observations of lying/standing behaviour. The statistical change detection algorithm that is used for this oestrus detection should be tested on a more extensive dataset in order to fully verify the results. Furthermore it would be interesting to utilise a real time test where the detection alarms would be used as decision support for insemination. Utilising a test in an operating stable and using the algorithm as basis for decision making on inseminations would show the ability to detect oestrus cases that otherwise would not be detected.

Observing the results of the lameness detection it is clear that the results are promising. Detecting lameness is difficult, especially the mild stages of the lameness. The next steps in the development should include tests of the algorithm using data from positioning devices instead of data from feeding boxes. Using positioning, it can be estimated from the position whether the cow is eating. The investigation should assess whether the cheap position estimates can replace the data, on duration of visits to the feeding boxes and the number of visits, delivered by the much more expensive feeding boxes.

CHAPTER 5

Summary of papers

The part with attached papers includes 5 publications. The first 4 publications (Papers A, B, C and D) describe oestrus detection using statistical change detection and automata theory. The last paper (Paper E) comprises lameness detection using maximum likelihood classification.

Below is a brief description of each of the 5 publications.

Paper A: This paper comprises statistical change detection on observations of activity for detecting oestrus in dairy cows. The activity was measured by an activity tag that was attached to the cows collar. Data sets of 6 months from 17 cows that were not in oestrus, were investigated for identifying distribution properties and diurnal activity. A recursive model that adapted to the diurnal activity of the individual was derived for removing the daily variation in the activity. Change detection algorithms were designed for the actual probability densities, which were Rayleigh distributed with individual parameters for each cow. A generalized likelihood ratio algorithm was derived for the compensated activity signal and detection algorithm was tested on 2323 days of activity, which contained 42 oestruses on 12 cows in total. The application of statistical change detection methods is a new approach for detecting oestrus in dairy cows and the results are shown to perform well with respect to combined statistics of false alarms and missed detections.

Paper B: This paper addresses detection of oestrus in dairy cows with models of lying/standing behaviour using automata-based modelling and diagnosis. Mea-

suring lying/standing behaviour of the cows by a sensor attached to the cows hindleg, lying/standing behaviour is modelled as a stochastic automaton. The paper introduces a cow's lying-balance as a biologically inspired quantity describing how much the cow has been resting for a preceding period. A dynamic lying-balance model is identified from real data and the lying balance is used as input, together with lying/standing sensor measurements. Using different automata models for oestrus and non-oestrus conditions, with state transition probability densities identified from observations, diagnosis theory for stochastic automata is employed to obtain diagnoses of oestrus. The oestrus cases are detected using consistency based diagnosis on real data.

Paper C: This paper describes an algorithm for detecting oestrus in dairy cows combining measurements of activity and duration of lying/standing periods using automata-based modelling and diagnosis. Automata for describing the two scenarios; normal and oestrus are designed and results of decision algorithms are presented for Oestrus detection. Detection based on the lying balance indicator and the two sets of measured information are demonstrated to increase the detection sensitivity to 100% for a set of 10 cows.

Paper D: Aiming at improving detection scheme reliability with the use of low-cost sensor data, this study combines information from step count and leg tilt sensors. Introducing a lying balance for the individual animal, a novel change detection scheme is derived from observed distributions of the step count data and the lying balance. Detection and hypothesis testing are based on generalised likelihood ratio optimisation combined with time-wise joint probability windowing based on the duration of oestrus and oestrus intervals. Test statistics are derived on-line from data and cow-specific parameter estimation is shown to be essential. Performance is validated on data selected from 8 months observations of 88 dairy cows wearing step count and leg tilt sensors. The results show detection performance among the best reported, the lowest false detection ratio yet reported when only cheap sensor data are used.

Paper E: Observations on behaviour are utilized to detect lameness in dairy cows. The aim is to enable an automatic lameness detection using only behavioural observations that were obtainable using low-cost sensors. Manual observations on the cows lameness state were available with approximately two weeks interval. These observations are taken to be the "truth". The used sensors are for observing activity, feeding behaviour and milking behaviour. Visits to feeding boxes were split into meals using earlier published methods. A maximum likelihood classification was used to classify the observations of behaviour into the two classes *lame* or *not lame*. The number of meals as well as the duration and intake during an interval were used in the classification. The classification was tested using different number of traits and data records from the days before the days where manual lameness observations were performed. The

classification algorithm used estimated posterior probabilities of several days before each manual observation to enhance the probability of detection and to reduce the probability of false alarms. The results showed that 71.4% of the lameness cases were detected on the day before a staff observation, with a specificity of 74.1%, using only the number of meals within an interval and the duration of meals within an interval. Adding intake rate, results improved to the extent that 76.1% of the lameness cases were detected on the day before a staff observation, with as slightly reduced specificity of 73.1%.

Bibliography

R. Alur and D.L. Dill. A theory of timed automata. *Theoretical Computer Science*, 126(2):183–235, 1994. ISSN 03043975.

A. Bach, M. Dinares, M. Devant, and X. Carre. Associations between lameness and production, feeding and milking attendance of holstein cows milked with an automatic milking system. *Journal of Dairy Research*, 74(1):40–46, 2007. ISSN 00220299.

M. Basseville and I. V. Nikiforov. *Detection of Abrupt Changes: Theory and Application*. Information and System Science. Prentice Hall, New York, 1993.

N. Beusker. *Welfare of Dairy Cows: Lameness in Cattle - A Literature Review*. PhD thesis, Tierärztliche Hochschule Hannover, 2007.

M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki. *Diagnosis and Fault-Tolerant Control*. Springer, 2 edition, 2006.

C. J. Booth, L. D. Warnick, Y. T. Grohn, D. O. Maizon, C. L. Guard, and D. Janssen. Effect of lameness on culling in dairy cows. *Journal of Dairy Science*, 87(12):4115–4122, 2004. ISSN 00220302.

T. F. Borderas, A. Fournier, J. Rushen, and A. M. B. De Passille. Effect of lameness on dairy cows' visits to automatic milking systems. *Canadian Journal of Animal Science*, 88(1):1–8, 2008. ISSN 00083984.

C. G. Cassandras and S. Lafortune. *Introduction to Discrete Event Systems*. Springer, 2 edition, 2008.

J. Cavalieri, V. E. Eagles, M. Ryan, and K. L. MacMillan. Comparison of four methods for detection of oestrus in dairy cows with resynchronised oestrous cycles. *Australian Veterinary Journal*, 81(7):422–425, 2003.

M. A. Crowe. Resumption of ovarian cyclicity in post-partum beef and dairy cows. *Reproduction in Domestic Animals*, 43(s5):20–28, 2008.

H. Dobson, S. L. Walker, M. J. Morris, J. E. Routly, and R. F. Smith. Why is it getting more difficult to successfully artificially inseminate dairy cows? *animal*, 2(08):1104–1111, 2008. doi: 10.1017/S175173110800236X.

W. J. Eradus and M. B. Jansen. Animal identification and monitoring. *Computers and Electronics in Agriculture*, 24(1/2):91–98, 1999.

W. J. Eradus, W. Rossing, P. H. Hogewerf, and E. Benders. Signal processing of activity data for oestrus detection in dairy cattle. Wageningen, Netherlands, 1992.

W. J. Eradus, H. Scholten, and A. J. Udink-ten Cate. Oestrus detection in dairy cattle using a fuzzy inference system. *Control applications and ergonomics in agriculture CAEA ' 98: A Proceedings volume from the IFAC Workshop, Athens, Greece, 14 17 June 1998*, 1999.

L. A. Espejo, M. I. Endres, and J. A. Salfer. Prevalence of lameness in high-producing holstein cows housed in freestall barns in minnesota. *Journal of Dairy Science*, 89(8):3052–3058, 2006. ISSN 00220302.

J. F. Ettema and S. Østergaard. Economic decision making on prevention and control of clinical lameness in danish dairy herds. *Livestock Science*, 102(1-2): 92–106, 2006. ISSN 18711413.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Automation of oestrus detection in dairy cows: a review. *Livestock Production Science*, 75(3):219–232, 2002.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Improving oestrus detection by combination of activity measurements with information about previous oestrus cases. *Livestock Production Science*, 82(1):97–103, 2003a.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Oestrus detection in dairy cows based on serial measurements using univariate and multivariate analysis. *Archiv fur Tierzucht*, 46(2):127–142, 2003b.

F. C. Flower and D. M. Weary. Effect of hoof pathologies on subjective assessments of dairy cow gait. *Journal of Dairy Science*, 89(1):139–146, 2006. ISSN 00220302.

F. C. Flower, D. J. Sanderson, and D. M. Weary. Hoof pathologies influence kinematic measures of dairy cow gait. *Journal of Dairy Science*, 88(9):3166–3173, 2005. ISSN 00220302.

R. H. Foote. Time of artificial insemination and fertility in dairy cattle. *Journal of Dairy Science*, 62(2):355–358, 1979. ISSN 00220302.

N C Friggens, M Bjerring, C Ridder, S Højsgaard, and T Larsen. Improved detection of reproductive status in dairy cows using milk progesterone measurements. *Reproduction in Domestic Animals*, 43(s2):113–121, 2008.

L. A. Gonzalez, B. J. Tolkamp, M. P. Coffey, A. Ferret, and I. Kyriazakis. Changes in feeding behavior as possible indicators for the automatic monitoring of health disorders in dairy cows. *Journal of Dairy Science*, 91(3): 1017–1028, 2008. ISSN 00220302.

F. Gustafsson. *Adaptive Filtering and Change Detection*. John Wiley & Sons, Ltd, 2000.

J. Hernandez, J. K. Shearer, and D. W. Webb. Effect of lameness on the calving-to-conception interval in dairy cows. *Journal of the American Veterinary Medical Association*, 218(10):1611–1614, 2001. ISSN 00031488.

J. A. Hernandez, E. J. Garbarino, J. K. Shearer, C. A. Risco, and W. W. Thatcher. Comparison of milk yield in dairy cows with different degrees of lameness. *Journal of the American Veterinary Medical Association*, 227(8): 1292–1296, 2005. ISSN 00031488.

J.S. Hunter. The exponentially weighted moving average. *Journal of Quality Technology*, 18(4):203–210, 1986. ISSN 00224065.

R. Jónsson. Modelling cow behaviour using stochastic automata. Technical Report 2010.03, Institute of Automation and Computer Control, Ruhr-Universität Bochum, Universitätsstraße 150, 44780 Bochum, January 2010.

R. I. Jónsson, T. Björgvinsson, M. Blanke, N. K. Poulsen, S. Højsgaard, and L. Munksgaard. Oestrus detection in dairy cows using likelihood ratio tests. In *Proceedings of the 17th World Congress, The International Federation of Automatic Control, Seoul, Korea, July 6-11, 2008*, 2008.

S. M. Kay. *Fundamentals of Statistical Signal Processing, Volume 2: Detection Theory*. Prentice-Hall, 1998.

C. A. Kiddy. Variation in physical activity as an indication of oestrus in dairy cows. *Journal of Dairy Science*, 60:235–243, 1977.

O. Kocak and B. Ekiz. The effect of lameness on milk yield in dairy cows. *Acta Veterinaria Brno*, 75(1):79–84, 2006. ISSN 00017213.

R. K. Koelsch, D. J. Aneshansley, and W. R. Butler. Analysis of activity measurement for accurate oestrus detection in dairy cattle. *Journal of Agricultural Engineering Research*, 58(2):107–114, 1994.

E. Kramer, D. Cavero, E. Stamer, and J. Krieter. Mastitis and lameness detection in dairy cows by application of fuzzy logic. *Livestock Science*, 125(1): 92–96, 2009. ISSN 18711413.

X Liu and S-L Spahr. Automated electronic activity measurement for detection of estrus in dairy cattle. *Journal of Dairy Science*, 76(10):2906–2912, 1993.

N. Livshin, J. Grinshpun, L. Rpsenfeld, I. Shvartzman, A. Antler, B. Zion, G. Stojanovski, G. Bunevski, and E. Maltz. Lying behaviour of dairy cows under different housing systems and physiological conditions. *Precision Livestock Farming '05*, pages 305–311, 2005.

J. Lunze and J. Schröder. State observation and diagnosis of discrete-event systems described by stochastic automata. *Discrete Event Dynamic Systems*, 11(4):319–369, 2001.

N. Lynch. I/o automata: A model for discrete event systems. Technical report, Massachusetts Institute of Technology, Laboratory for Computer Science, 1988.

K. Maatje, M. de Mol, R., and W. Rossing. Cow status monitoring (health and oestrus) using detection sensors. *Computers and Electronics in Agriculture*, 16(3):245–254, 1997.

J.F. MacGregor. The exponentially weighted moving variance. *Journal of Quality Technology*, 25(2):106–118, 1993. ISSN 00224065.

H. Mazrier, S. Tal, E. Aizinbud, and U. Bargai. A field investigation of the use of the pedometer for the early detection of lameness in cattle. *Canadian Veterinary Journal*, 47(9):883, 2006. ISSN 00085286.

M. de Mol, R. and E. Woldt, W. Application of fuzzy logic in automated cow status monitoring. *Journal of Dairy Science*, 84(2):400–410, 2001.

M. de Mol, R., H. Kroeze, G., M. F. H. Achten, J., K. Maatje, and W. Rossing. Results of a multivariate approach to automated oestrus and mastitis detection. *Livestock Production Science*, 48(3):219–227, 1997.

M. de Mol, R., A. Keen, H. Kroeze, G., and M. F. H. Achten, J. Description of a detection model for oestrus and diseases in dairy cattle based on time series analysis combined with a kalman filter. *Computers and Electronics in Agriculture*, 22(2/3):171–185, 1999.

A. S. Moore and S. L. Spahr. Activity monitoring and an enzyme immunoassay for milk progesterone to aid in the detection of estrus. *Journal of Dairy Science*, 74(11):3857–3862, 1991.

I. Mozetic. Hierarchical model-based diagnosis. *International Journal of Man-Machine Studies*, 35(3):329–362, 1991. ISSN 00207373.

L. Munksgaard, C. G. Reenen, and R. Boyce. Automatic monitoring of lying, standing and walking behavior in dairy cattle. *Journal of Animal Science, Conference Supplement*, 84:304, 2006.

L. Nebel, R., G. Dransfield, M., M. Jobst, S., and H. Bame, J. Automated electronic systems for the detection of oestrus and timing of ai in cattle. *Animal Reproduction Science*, 60/61:713–723, 2000.

K. O'Callaghan. Lameness and associated pain in cattle – challenging traditional perceptions. *In Practice - Borough Green*, 24(4):212, 2002. ISSN 0263841x.

K. A. O'Callaghan, P. J. Cripps, D. Y. Downham, and R. D. Murray. Subjective and objective assessment of pain and discomfort due to lameness in dairy cattle. *Animal Welfare*, 12(4):605–610, 2003. ISSN 09627286.

J. O'Connell, F. Tøgersen, N. Friggens, P. Løvendahl, and S. Højsgaard. Combining cattle activity and progesterone measurements using hidden semi-markov models. *Journal of Agricultural, Biological, and Environmental Statistics*, 16:1–16, 2011. ISSN 1085-7117.

M. Pastell, H. Takko, H. Grohn, M. Hautala, V. Poikalainen, J. Praks, I. Veermae, M. Kujala, and J. Ahokas. Assessing cows' welfare: weighing the cow in a milking robot. *Biosystems Engineering*, 93(1):81–87, 2006. ISSN 15375110.

M. Pastell, M. Hautala, V. Poikalainen, J. Praks, I. Veermäe, M. Kujala, and J. Ahokas. Automatic observation of cow leg health using load sensors. *Computers and Electronics in Agriculture*, 62(1):48–53, 2008. ISSN 01681699.

M. E. Pastell and M. Kujala. A probabilistic neural network model for lameness detection. *Journal of Dairy Science*, 90(5):2283–2292, 2007. ISSN 00220302.

O. A. Peralta, R. E. Pearson, and R. L. Nebel. Comparison of three estrus detection systems during summer in a large commercial dairy herd. *Animal Reproduction Science*, 87(1-2):59–72, 2005. ISSN 03784320.

A. S. Poznyak and K. Najim. *Learning Automata and Stochastic Optimization*. Springer, 1997.

R. J. Pulvermacher and K. Maatje. Influence of threshold values and duration of increased activity on the prediction of oestrus by pedometers. 1992.

P. G. Rajkondawar, U. Tasch, A. M. Lefcourt, B. Erez, R. M. Dyer, and M. A. Varner. A system for identifying lameness in dairy cattle. *Applied Engineering in Agriculture*, 18(1):87–96, 2002. ISSN 08838542.

P. G. Rajkondawar, M. Liu, R. M. Dyer, N. K. Neerchal, U. Tasch, A. M. Lefcourt, B. Erez, and M. A. Varner. Comparison of models to identify lame cows based on gait and lesion scores, and limb movement variables. *Journal of Dairy Science*, 89(11):4267–4275, 2006. ISSN 00220302.

K. D. Redden, A. D. Kennedy, J. R. Ingalls, and T. L. Gilson. Detection of estrus by radiotelemetric monitoring of vaginal and ear skin temperature and pedometer measurements of activity. *Journal of Dairy Science*, 76(3):713–721, 1993.

J. B. Roelofs, F. J. C. M. van Eerdenburg, W. Hazeleger, N. M. Soede, and B. Kemp. Pedometer readings for estrous detection and as predictor for time of ovulation in dairy cattle. *Theriogenology*, 64(8):1690–1703, 2005a.

J. B. Roelofs, F. J. C. M. van Eerdenburg, W. Hazeleger, N. M. Soede, and B. Kemp. Various behavioral signs of estrous and their relationship with time of ovulation in dairy cattle. *Theriogenology*, 63(5):1366 – 1377, 2005b. ISSN 0093-691X.

D. Schlünsen, H. Roth, H. Schön, W. Paul, and H. Speckmann. Automatic health and oestrus control in dairy husbandry through computer aided systems. *Journal of Agricultural Engineering Research*, 38(4):263–279, 1987. ISSN 00218634.

S. A. Schofield, C.J.C. Phillips, and A. R. Owens. Variation in milk production, activity rate and electrical impedance of cervical mucus over the oestrus period of dairy cows. *Animal Reproduction Science*, 24:231–248, 1991.

J. Schröder. *Modelling, State Observation and Diagnosis of Quantised Systems.* Lecture Notes in Control and Information Sciences, 2003.

X. Song, T. Leroy, E. Vranken, W. Maertens, B. Sonck, and D. Berckmans. Automatic detection of lameness in dairy cattle-vision-based trackway analysis in cow's locomotion. *Computers and Electronics in Agriculture*, 64(1):39–44, 2008. ISSN 01681699.

P. Supavatanakul. *Modelling and Diagnosis of Timed Discrete-Event Systems.* PhD thesis, Lehrstuhl für Automatisierungstechnik und Prozessinformatik, Ruhr-Universität Bochum, 2004.

P. T. Thomsen, L. Munksgaard, and F. A. Tøgersen. Evaluation of a lameness scoring system for dairy cows. *J. Dairy Sci.*, 91(1):119–126, 2008.

F. J. C. M. van Eerdenburg, D. Karthaus, M. A. M. Taverne, I. Merics, and O. Szenci. The relationship between estrous behavioral score and time of ovulation in dairy cattle. *Journal of Dairy Science*, 85(5):1150–1156, 2002. ISSN 00220302.

S. L. Walker, R. F. Smith, J. E. Routly, D. N. Jones, M. J. Morris, and H. Dobson. Lameness, activity time-budgets, and estrus expression in dairy cattle. *Journal of Dairy Science*, 91(12):4552–4559, 2008. ISSN 00220302.

L. D. Warnick, D. Janssen, C. L. Guard, and Y. T. Grohn. The effect of lameness on milk production in dairy cows. *Journal of Dairy Science*, 84(9):1988–1997, 2001. ISSN 00220302.

D. W. Webb. Artificial insemination in dairy cattle. Technical report, The Animal Science Department, Florida Cooperative Extension Service, Institute of Food and Agricultural Sciences, University of Florida, 2003.

G. Wendl and K. Klindtworth. Einsatz von elektronischen schrittzählern (pedometer) zur brunsterkennung bei milchkühen. 1997.

H. Whay. Locomotion scoring and lameness detection in dairy cattle. *In Practice - Borough Green*, 24(8):444, 2002. ISSN 0263841x.

H. R. Whay, D. C. J. Main, L. E. Green, and A. J. F. Webster. Assessment of the welfare of dairy cattle using animal-based measurements: direct observations and investigation of farm records. *Veterinary Record - English Edition*, 153 (7):197, 2003. ISSN 00424900.

W. F. Williams, D. R. Yver, and T. S. Gross. Comparison of oestrus detection techniques in dairy heifers. *Journal of Dairy Science*, 64:1738–1741, 1981.

H. A. Zarchi, R. I. Jónsson, and M. Blanke. Improving oestrus detection in dairy cows by combining statistical detection with fuzzy logic classification. In *Proceedings of the 7th Workshop on Advanced Control and Diagnosis, Zielona Gora, Poland, 2009*, 2009.

Publications

PAPER A

Oestrus Detection in Dairy Cows Using Likelihood Ratio Tests[1]

Jónsson, R. I., Björgvinsson, T., Blanke, M., Poulsen, N. K., Højsgaard, S. and Munksgaard, L.

Abstract

This paper addresses detection of oestrus in dairy cows using methods from statistical change detection. The activity of the cows was measured by a necklace attached sensor. Statistical properties of the activity measure were investigated. Using data sets from 17 cows, diurnal activity variations were identified for the ensemble and for the individual cows. A diurnal filter was adapted to remove the daily variation of the individual. Change detection algorithms were designed for the actual probability densities, which were Rayleigh distributed with individual parameters for each cow. A generalized likelihood ratio algorithm was derived for the compensated activity signal and detection algorithm was tested on 2323 days of activity, which contained 42 oestruses on 12 cows in total. The application of statistical change detection methods is a new approach for detecting oestrus in dairy cows and the results are shown to perform well with respect to combined statistics of false alarms and missed detections.

A.1   Introduction

Early detection of oestrus in cows is very important for modern highly efficient farmers. The reproductive cycle of dairy cows is about 21 days, but typically varies from 18 to 23 days. Roughly speaking, insemination should take place within 6-12 hours after ovulation. Visual detection of oestrus is a difficult task and requires highly skilled personnel. Even with experienced personnel, the success rate in visual detection is relatively low, about 60%. Modern dairy farms can have several hundred cows and with labor being expensive in most European countries there is less and less time for focusing on each individual animal. Therefore there is a need for alternative reliable and economical methods of oestrus detection.

There are several indicators (of varying importance) of oestrus. Increased physical activity has often been pointed out as one of the indicators of oestrus. Kiddy [1977] investigated the variation in physical activity as an indication of oestrus and found that on average the activity at oestrus was about 4 times the normal activity. Schlünsen et al. [1987] found that step activity in loose housing with cubicles doubled during the oestrus.

Numerous studies have been conducted on the subject of automatic oestrus detection in dairy cows. Many authors, e.g. Moore and Spahr [1991], Liu and Spahr [1993] and Roelofs et al. [2005], have used simple statistical tests where a mean of recent activity is compared to an older mean of activity. Analysis of time series where parameters were updated by means of a Kalman filter was performed by Maatje et al. [1997], Mol et al. [1997] and Mol et al. [1999]. Further, Eradus et al. [1999], Mol and Woldt [2001] and Firk et al. [2003b] detected oestrus by Fuzzy logic methods.

Methods of automated oestrus detection have been reviewed by Eradus and Jansen [1999], Nebel et al. [2000] and Firk et al. [2002]. Comparison of commercial systems was done by Cavalieri et al. [2003] and Peralta et al. [2005].

Change detection and fault diagnosis based on likelihood ratio tests have proven beneficial in many areas as error detection tools, see e.g. Basseville and Nikiforov [1993], Gustafsson [2000]. However, these methods have not been used earlier for detection of oestrus in dairy cattle. The reasons include the difficulties in real-time monitoring on a large number of live animals, an instrumentation issue, that is now being solved.

Activity sensor data were avialable from the Danish Cattle Research Center in Foulum, Denmark. The data set comprised real-time monitoring of 111 cows over a six months period. This paper scrutinizes activity sensor data and suggest

algorithms for the detection of oestrus in dairy cows using likelihood hypothesis tests. Specifically, this paper describes analysis of activity data and the preprocessing necessary to derive a residual for change detection, compensating for diurnal variation in data. Properties of different residuals are discussed and through identifying probability distribution properties, a dedicated change detection and hypothesis test algorithm is derived. Results from tests of the detection algorithm are presented and the properties are compared with those published on other methods from the literature.

A.2   Data

The data consist of measurements of activity on cows in a loose housing with cubicles. The activity data were recorded at the Danish Cattle Research Center over a period of 6 months ("the study period").The activity was measured by means of commercial activity tags placed on the cows neck. The activity sensors ALPRO® by DeLaval return an activity index for each hour.

The original dataset consisted of data for 111 cows. Data from 82 cows which had either received a medical treatment during the study period or had long time periods of missing data observations were discarded. The reason for discarding data for cows that had received medical treatment was to eliminate possible effects on the activity resulting from identified diseases. Of the remaining 29 cows, 17 were pregnant during the entire study period and did hence not go into oestrus. This leaves a group of 12 cows of which 9 became pregnant during the study period. Each of these were inseminated once or more during the study period. Data belonging to the 12 cows, that were inseminated was used for testing the detection algorithm.

Data belonging to the 17 cows that were categorized as pregnant during the study period were considered as being normal behaving, as they received no medical treatment and did not go into oestrus in the study period. Data belonging to these cows was used for identification of data properties for normal behaviour, e.g. distribution properties, autocorrelation, power spectrum etc..

To validate the method we took the following approach: Oestrus occurs around the time of ovulation. The precise time of ovulation can not be measured in practice. Therefore we have to base the evaluation on observable quantities known to be related to the time of ovulation. Visual inspection of the acitivity level of the cows is one such option which is based on that cows have a higher activity level around the time of ovulation. A better solution to the issue would be to find assumed oestrus cases from milk progesterone measurements. This is

Table A.1: Number of days of activity data and number of assumed oestruses for cows which were inseminated.

Cow No.	No. of Activity Days	No. of oestrus ref.
34	195	1
224	195	2
244	195	1
307	195	1
334	195	7
353	178	2
371	195	2
373	195	4
494	195	4
1198	195	3
1246	195	9
1253	195	4
Total	2323	42

more or less the accepted "gold standard" for identifying oestrus cases Friggens et al. [2008]. Unfortunately milk progesterone measurements were not available for this study, hence visual observations were used. Additional assumed oestrus cases were chosen in the period 18-23 days after a performed insemination if the assumed oestrus case in question was followed by an insemination or a registered observation 18-23 days later.

For the purpose of this study the exact time of assumed oestrus is determined as the middle of a 24[] window that has the greatest activity sum in a 48[] space around the day of insemination. This is found by evaluating

$$k_{ot} = \operatorname*{arg\,max}_{k_r - 24 \le j \le k_r + 24} \sum_{i = j - \frac{24}{2}}^{j + \frac{24}{2}} y(i) \tag{1}$$

where k_{ot} is the estimated time of assumed oestrus, k_r is the sample number at midnight the day before assumed oestrus and $y(i)$ is the activity index at sample i. The estimated time of assumed oestrus is used to plot the assumed oestruses in graphs and to have a time reference to use for comparison of different versions of the algorithm with respect to how fast the detection algorithm is.

Table A.1 shows the number of days of activity data and the number of assumed oestruses for each cow in oestrus as well as the total days of activity data and the total number of assumed oestruses for the 12 "cows in oestrus".

As an example of the activity data, Figure A.1 shows a plot of the activity data
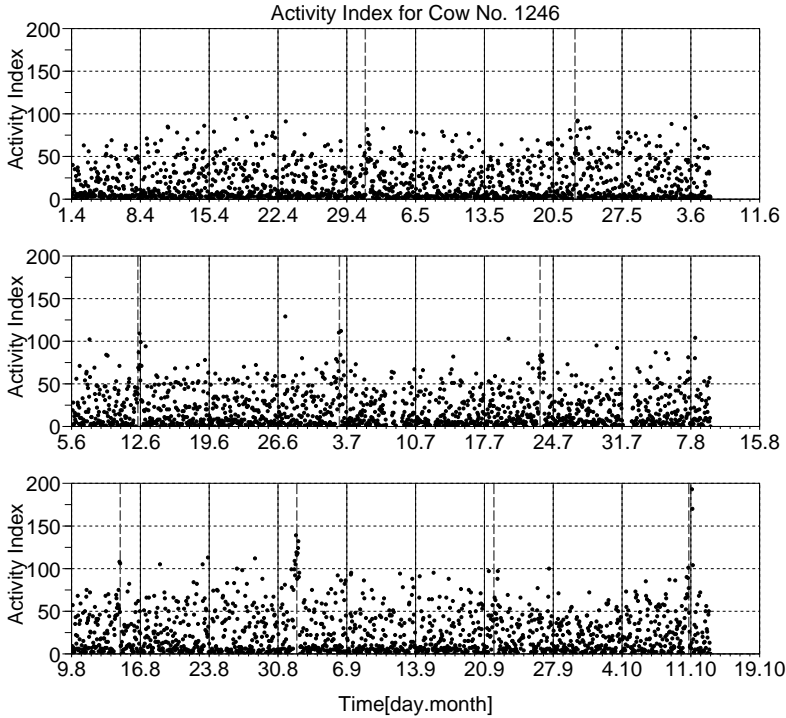
Figure A.1: Activity index for cow no. 1246.

for cow no. 1246 which belongs to the group of cows that were inseminated once or more during the study period. The activity index is shown as black dots and assumed oestruses are shown as dashed vertical lines.

A histogram of a cow which had no insemination during the study period (cow no. 358) is shown in the figure on the left in Figure A.2. The histogram shows that the activity data are right skewed with considerable point mass in zero. Hence, a transformation, e.g. a logarithmic transformation, of data does not produce normally distributed data either (see Figure A.2).

A.3   Problem

This section assigns the derivation of the change detection algorithm and the elimination of periodic oscillations in the activity signal. The elimination of the periodic oscillations is described in A.3.1 and the derivation of the change detection algorithm is described in A.3.2.
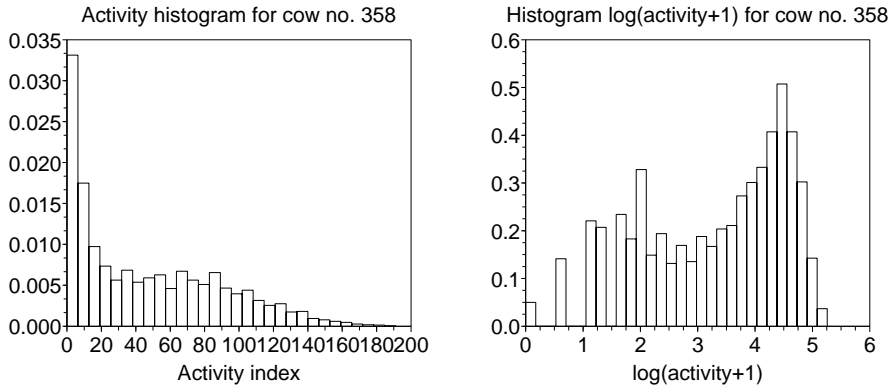
Figure A.2: Activity histogram and histogram of $\log(activity + 1)$ for cow no. 358.

A.3.1 Residual Generator

Because cows move around, rest, eat, sleep, interact with other individuals etc., some sort of diurnal variations in the activity signal can be expected. These variations are unwanted in the signal as the decision system is to detect other kinds of variations in the activity signal i.e. increased activity in connection with oestrus. These diurnal variations were modelled and eliminated by means of a regression model where the diurnal variations were expressed by trigonometric functions.

The frequencies used to describe the diurnal variations were found by identifying the frequencies where the activity carries higher power in a power spectral density plot. A significance test of the compensation of the chosen frequencies was performed.

A.3.1.1 Modelling of Diurnal Oscillations

Power spectral density plots showed that the activity data for the 17 pregnant cows in most cases had increased power at frequencies corresponding to periods of 24, 12, 8, 6, 4.8 and 4 hours. Figure A.3 shows the power spectrum of the activity for cow no. 358.
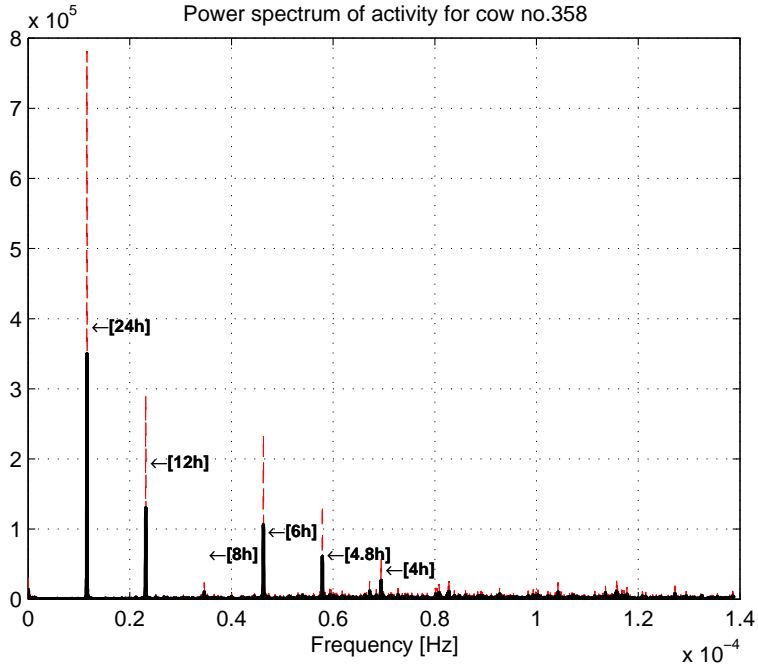
Figure A.3: Power spectrum of activity for cow no. 358.

A cows daily activity is described as a linear model by the following expression.

$$
\begin{aligned}
y(k) \quad = \quad & \mu + A_1 \cos(\omega_1 k) + B_1 \sin(\omega_1 k) + \ldots \\
& + A_m \cos(\omega_m k) + B_m \sin(\omega_m k) + \varepsilon(k)
\end{aligned}
\tag{2}
$$

where μ is the mean activity and ε is the noise component. On vector form it becomes.

$$
\mathbf{Y} = \mathbf{\Phi}\theta + \varepsilon
\tag{3}
$$

where

$$
\mathbf{\Phi} = \begin{bmatrix} 1 & \cos(\omega_1 k) & \sin(\omega_1 k) & \ldots & \cos(\omega_m k) & \sin(\omega_m k) \end{bmatrix}
\tag{4}
$$

and

$$
\theta^T = \begin{bmatrix} \mu & A_1 & B_1 & \ldots & A_m & B_m \end{bmatrix}
\tag{5}
$$

The model coefficients are found by using the least squares method where the cost function $J_N(\theta) = \frac{1}{2}\varepsilon^T \varepsilon$ is minimized. The estimated coefficients are found as

$$
\hat{\theta} = \left(\mathbf{\Phi}^T \mathbf{\Phi} \right)^{-1} \mathbf{\Phi}^T \mathbf{Y}
\tag{6}
$$

This leaves us to the residual

$$\hat{\varepsilon} = \mathbf{Y} - \phi\hat{\theta} \tag{7}$$

The significance of each estimated coefficient in the model is investigated by an F-test. The F-test is used under the assumption, that the residuals are uncorrelated, are normally distributed and that the variance is constant. While these assumptions are not formally met the F-test still gives indication of the importance of each component in the model. Starting with only the intercept, pairs of components of the form $(A_m \cos(\omega_m k), B_m \sin(\omega_m k))$ where $m = (n - 1)/2$ were added to the model.

Let $J(\hat{\theta}_a)$ be the cost function for the current model and let $J(\hat{\theta}_b)$ be the cost for the model with a pair of components added. Then the F-statistic for adding this pair of components becomes

$$g = \frac{J(\hat{\theta}_a) - J(\hat{\theta}_b)}{J(\hat{\theta}_b)} \times \frac{N - n_b}{n_b - n_a} \tag{8}$$

where N is the number of observations and n_a and n_b are the number of coefficients in the current model and in the model with a pair of components added, respectively. Under the hypothesis that the pair of components do not contribute significantly the statistic g has an F-distribution $g \sim F(n_b - n_a, N - n_b)$ and the hypothesis is rejected if

$$g > f_{1-\alpha}^F(n_b - n_a, N - n_b) \tag{9}$$

where $f_{1-\alpha}^F$ is a quantile in the F-distribution at $\alpha = 0.01$. The results of the F-test performed on activity data for the 17 cows that were pregnant during the study period are shown in Table A.2. Here $n_{sign.}$ corresponds to the number of cows where the reduction in the cost function is significant and n_{cows} corresponds to the total number of cows regarded in the test. It can be seen from Table A.2 that the addition of components corresponding to each frequency in the model results in a significant reduction in the cost function for all of the tested cows except for the addition of components for periods of 8[] and 4[]. In these two latter cases the reduction in the cost function is significant for 83% and 78% of the tested cows, respectively. It is therefore concluded that the estimation of components for all the tested frequencies is significant for a majority of the tested cows and should therefore be included in the regression model that is used in this study. The on-line version of the regression model that was used in the study includes a recursive least squares estimator with a forgetting factor. In the recursive version the model coefficients are for each cow found as

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \mathbf{K}(k)\left(y(k) - \mathbf{\Phi}(k)\hat{\theta}(k-1)\right) \tag{10}$$

where

$$\mathbf{K}(k) = \mathbf{P}(k)\mathbf{\Phi}^T(k) \tag{11}$$

Table A.2: Significance test of estimated coefficients in the regression model at 99% quantile

$\hat{\bar{g}}$	$\hat{\sigma}_g$	Quantile	$\frac{n_{sign.}}{n_{cows}}$	n	T[]
197.67	107.27	4.61	1.00	3	24
55.27	35.99	4.61	1.00	5	24, 12
12.64	8.26	4.61	0.83	7	24, 12, 8
69.45	38.03	4.61	1.00	9	24, 12, 8, 6
29.60	15.71	4.61	1.00	11	24, 12, 8, 6, 4.8
15.34	9.88	4.61	0.78	13	24, 12, 8, 6, 4.8, 4

and

$$\mathbf{P}(k) = \left(\mathbf{P}(k-1) - \frac{\mathbf{P}(k-1)\mathbf{\Phi}^T(k)\mathbf{\Phi}(k)\mathbf{P}(k-1)}{\lambda + \mathbf{\Phi}(k)\mathbf{P}(k-1)\mathbf{\Phi}^T(k)} \right) \frac{1}{\lambda} \tag{12}$$

where $P(k)$ has to be non singular. The on line calculation of the residual is therefore

$$\hat{\varepsilon}(k) = y(k) - \mathbf{\Phi}(k)\hat{\theta}(k) \tag{13}$$

A.3.1.2 Identification of Residual Distribution Properties

Histograms of the residuals for the 17 pregnant cows show that the activity residuals for normal behaviour can be described by a Rayleigh density function shifted to match the mean value $\mu = 0$. Figure A.4 shows a histogram and a shifted Rayleigh density function for a cow that belongs to the group of "normal cows".

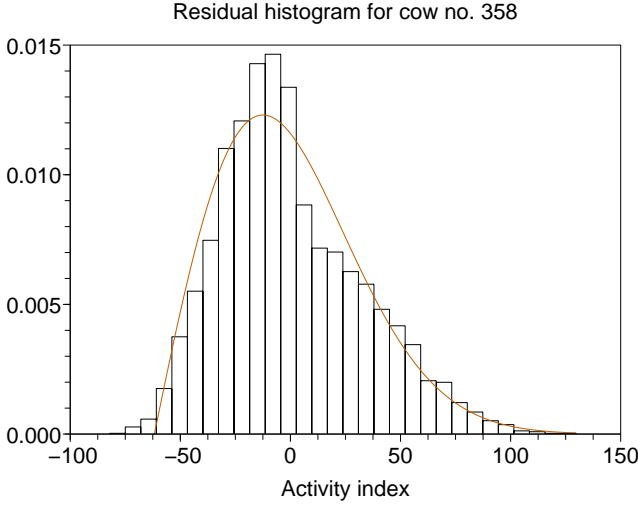The shifted Rayleigh density function has the form

$$p_{\mu 0}\left(\varepsilon(k)\right) = \frac{\varepsilon(k) + s\sqrt{\frac{\pi}{2}}}{s^2} \exp\left[-\frac{\left(\varepsilon(k) + s\sqrt{\frac{\pi}{2}}\right)^2}{2s^2} \right] \tag{14}$$

for

$$\varepsilon(k) \geq -s\sqrt{\frac{\pi}{2}} \ , \ s > 0$$

where s is the shape parameter and is found as

$$s = \sqrt{\frac{\sigma^2}{2 - \frac{\pi}{2}}} \tag{15}$$

Residual histogram for cow no. 358

Figure A.4: Residual histogram and an approximated Rayleigh density function for cow no. 358.

where σ^2 is the variance. This leads to the density function

$$p_{\mu 0}(\varepsilon(k)) = \frac{(4-\pi)\left(\varepsilon(k) + \frac{\sqrt{\sigma^2 \pi}}{\sqrt{4-\pi}}\right)}{2\sigma^2} \tag{16}$$

$$\times \exp\left[-\frac{\left(\varepsilon(k)\sqrt{4-\pi} + \sqrt{\sigma^2 \pi}\right)^2}{4\sigma^2}\right]$$

$$\text{for} \quad \varepsilon(k) \geq \quad -\frac{\sqrt{\sigma^2 \pi}}{\sqrt{4-\pi}} \ , \ \sigma^2 > 0$$

On-line variance estimation of the residual variance is done by an exponential estimation. In order to avoid influence from an increased variance in connection with an oestrus case the variance estimation uses a delayed signal. The variance estimation is written as
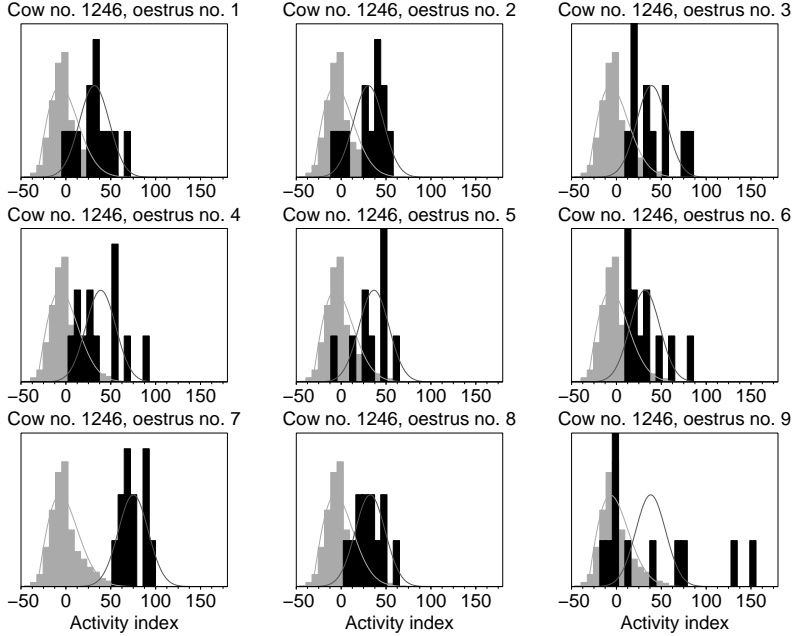
$$\hat{\sigma}^2(k) = \hat{\sigma}^2(k-1) + \frac{1}{T(k)}\left(\varepsilon(k-D_d)^2 - \hat{\sigma}^2(k-1)\right) \tag{17}$$

$$\text{for} \ \ l_l + D_h < k < l$$

$$\hat{\sigma}^2(k) = \hat{\sigma}^2(k-1) \ \ \text{for} \ \ l < k < l + D_h \tag{18}$$

$$T(k) = \lambda T(k-1) + 1 \tag{19}$$

where D_d is the estimation delay, l is the time of the actual oestrus detection, l_l

Figure A.5: Histograms of normal and oestrus activity and approximated
Rayleigh and gaussian density functions for the 9 oestrus cases
for cow no. 1246.

is the time of the last oestrus detection and D_h is the number of samples where
the estimation is halted after a detection.

As an ovulation is not expected to last longer than 24 hours the delay is chosen
as $D_d = 24$. The number of samples where the estimation is halted after a
detection is chosen as $D_h = 72$.

A.3.2   Likelihood Ratio Test

Activity data belonging to cows that were inseminated during the study period
were observed with respect to the change in activity during oestrus by classifying
the data into data belonging to normal activity and data belonging to oestrus
cases. This was done by extracting 24[] of data around k_{ot} (see (1)) for each
assumed oestrus out of the data series. A histogram of the data belonging to
each assumed oestrus was plotted in front of a histogram for the data belonging
to normal activity. Figure A.5 shows such histograms for cow no. 1246 which
had 9 assumed oestruses during the study period. The histograms of the data

belonging to normal activity is shown in light gray and the histograms belonging to each assumed oestrus are shown in black. The figure shows additionally a Rayleigh density function for the normal activity and a gaussian density function for the oestrus activity. Both density functions are plotted with the estimated variance of the normal activity.

By observing e.g. Figure A.5 it is concluded that a generalized likelihood algorithm (GLR) is a suitable algorithm for the likelihood ratio test. The GLR algorithm has a decision function that maximizes with respect to the change in mean, with μ_1 as the mean under deviant behaviour, and the time j for the on-set of fault of the form.

$$g(k) = \max_{1 \le j \le k} \max_{\mu_1} S_j^k(\mu_1) \tag{20}$$

The decision function where the normal activity is described by a shifted Rayleigh density function and oestrus activity is described by a gaussian density function was derived as

$$g(k) = \max_{k-M \le j \le k} \sum_{i=j}^{k} (\log \left(\frac{2\hat{\sigma}^2(i)}{\sqrt{2\pi\hat{\sigma}^2(i)}(4-\pi)\left(\varepsilon(i) + \frac{\sqrt{\pi\hat{\sigma}^2(i)}}{\sqrt{4-\pi}}\right)} \right)$$

$$-\frac{\left(\varepsilon(i) + \frac{\sum_{q=j}^{k} \frac{\varepsilon(q)}{\hat{\sigma}^2(q)}}{\sum_{q=j}^{k} \frac{1}{\hat{\sigma}^2(q)}}\right)^2}{2\hat{\sigma}^2(i)} + \frac{\left(\varepsilon(i)\sqrt{4-\pi} - \sqrt{\pi\hat{\sigma}^2(i)}\right)}{4\hat{\sigma}^2(i)}) \tag{21}$$

$$g(k) = 0 \quad for \quad \varepsilon(k) < -\frac{\sqrt{\sigma^2(k)\pi}}{\sqrt{4-\pi}} \tag{22}$$

where the fault occurrence time is restricted to the last M samples. As an oestrus case is not expected to last longer than 24[] M is determined as $M = 24[]$. A detection is initiated if $g(k) > h$ where h is the detection threshold.

An oestrus detection is in this study classified as being successful if the detection takes place within 24 [] before and after an assumed oestrus case. Mean time to detect $(\hat{T})$ is defined as the time delay between an assumed oestrus and the time of detection.

A.4   Results

Firk et al. [2002] classified the detections as true positives (TP) for successful detections and false positives (FP) for false detections. They classified non-detected oestrus cases as false negatives (FN) and inspections outside of oestrus
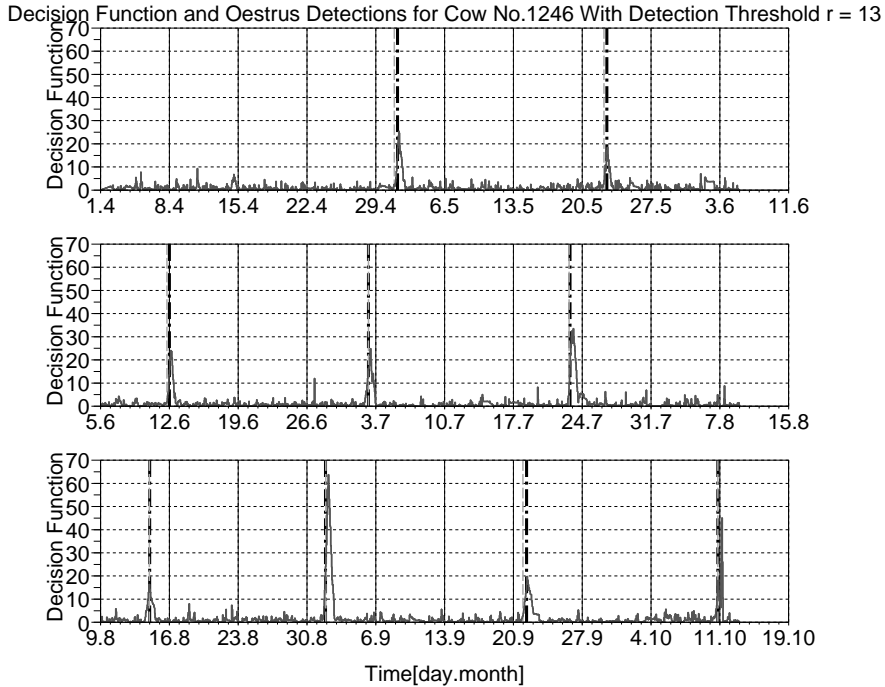
Figure A.6: Decision function for cow no. 1246.

with no detections as true negatives (TN). Number of true negatives are in this study defined as days outside of oestrus without a detection. Sensitivity, specificity and error rate are defined in e.g. Firk et al. [2002] and shown in Table A.3. Error rate is referred to as error ratio in this study.

The detection algorithm was tested on activity measurements belonging to the 12 cows that were in oestrus during the data period. The activity data was compensated for diurnal variations, using functions (10)-(13). and a decision value for each sample of measurement was calculated using the decision function in (21). The detection threshold was chosen manually for each cow. A more sophisticated version of the detection algorithm where the threshold is chosen automatically has not been developed yet, as the data sample used for this study is not sufficiently large for such a development.

Figure A.6 shows the decision function from the test performed on data for cow no. 1246. The activity index is shown as the solid dark gray line, detections are shown as dash-dotted vertical lines in black and assumed oestruses are dashed vertical lines in light gray.

Table A.3: Summary of detection results

Sensitivity [%]	Specificity [%]	Error ratio [%]
$\frac{TP}{TP+FN} \times 100$	$\frac{TN-FP}{TN} \times 100$	$\frac{FP}{TP+FP} \times 100$
$\frac{36}{36+6} \times 100 = 85.7$	$\frac{2323-6}{2323} \times 100 = 99.7$	$\frac{6}{36+6} \times 100 = 14.3$

Table A.4: Detection results

Cow No.	h	Sensitivity	Specificity	Error ratio	$\hat{\bar{T}}[]$
34	10	0.0	100.0%	-	-
224	9	100.0%	100.0%	0	-2
244	7	100.0%	100.0%	0	0
307	6	100.0%	100.0%	0	3
334	13	71.4%	100.0%	0	2.2
353	18	100.0%	100.0%	0	5
371	6.5	100.0%	99.5%	33.3%	4
373	5.5	75.0%	98.5%	50.0%	5
494	9	100.0%	100.0%	0	1
1198	20	66.7%	99.5%	33.3%	-5.5
1246	13	100.0%	100.0%	0	3.22
1253	9.5	75.0%	99.5%	25.0%	7.33

A summary of detections results for the entire group of cows studied are shown in Table A.3. The detection results for each of the 12 cows are shown in Table A.4. Mean time to detect was found as $\hat{\bar{T}} = 2.42$. Comparison of the detection results in Table A.3 with that of other authors reveal that the algorithm treated in this study performs very well with respect to detection ratio (sensitivity) and to number of false detections in particular.

Other authors that have used activity as the sole measurement are e.g. Firk et al. [2003b] and Roelofs et al. [2005]. Firk et al. [2003b] achieved sensitivity up to 94% with an error ratio of 53%. The best results presented with respect to error ratio had error ratio of 21% and sensitivity of 71%. Roelofs et al. [2005] achieved sensitivity up to 87% with an error ratio of 40%.

Several authors have combined multiple traits in their detection algorithms in order to obtain better detection results, e.g. Mol et al. [1997] and Firk et al. [2003a]. Mol et al. [1997] combined measurements on activity, milk yield, milk temperature, electrical conductivity and concentrate leftovers. They achieved sensitivity up to 95% with a specificity of 94%. The specificity is the result of 1488 false detections in 24219 inspections (inspections made twice a day). Their best results with respect to specificity was 98% (680 false detections in 34863

inspections) combined with a sensitivity of 82.5%. Firk et al. [2003a] combined measurements on activity with period from last oestrus. When considering cows with and without information on previous oestrus cases, the result was a sensitivity of 88.9% and an error ratio of 23.8%.

A.5 Conclusion

Using data sets from about 29 individuals, and compensating for diurnal activity variations for individual animals, statistical change detection theory was applied on oestrus detection in dairy cows. The detection algorithm was tested on 2323 days of activity, which contained 42 oestrus cases in 12 cows. The results were found to perform well with respect to combined results of false alarm and missed detection statistics when tuning detection parameters to individuals. However, further studies on a larger number of cows is needed.

Other forms of likelihood ratio tests, i.e. a change in activity described by a dynamic profile, were tested but did not result in improvements with respect to number of successful oestrus detections nor with respect to the number of false detections.

A.6 Acknowledgments

References

M. Basseville and I. V. Nikiforov. *Detection of Abrupt Changes: Theory and Application.* Information and System Science. Prentice Hall, New York, 1993.

J. Cavalieri, V. E. Eagles, M. Ryan, and K. L. MacMillan. Comparison of four methods for detection of oestrus in dairy cows with resynchronised oestrous cycles. *Australian Veterinary Journal*, 81(7):422–425, 2003.

W. J. Eradus and M. B. Jansen. Animal identification and monitoring. *Computers and Electronics in Agriculture*, 24(1/2):91–98, 1999.

W. J. Eradus, H. Scholten, and A. J. Udink-ten Cate. Oestrus detection in dairy cattle using a fuzzy inference system. *Control applications and ergonomics in agriculture CAEA ' 98: A Proceedings volume from the IFAC Workshop, Athens, Greece, 14 17 June 1998*, 1999.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Automation of oestrus detection in dairy cows: a review. *Livestock Production Science*, 75(3):219–232, 2002.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Improving oestrus detection by combination of activity measurements with information about previous oestrus cases. *Livestock Production Science*, 82(1):97–103, 2003a.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Oestrus detection in dairy cows based on serial measurements using univariate and multivariate analysis. *Archiv fur Tierzucht*, 46(2):127–142, 2003b.

N. C. Friggens, M. Bjerring, C. Ridder, S. Højsgaard, and T. Larsen. Improved detection of reproductive status in dairy cows using milk progesterone measurements. To appear in Reproduction in Domestic Animals, 2008.

F. Gustafsson. *Adaptive Filtering and Change Detection*. Wiley, 2000.

C. A. Kiddy. Variation in physical activity as an indication of oestrus in dairy cows. *Journal of Dairy Science*, 60:235–243, 1977.

X. Liu and S. L. Spahr. Automated electronic activity measurement for detection of estrus in dairy cattle. *Journal of Dairy Science*, 76(10):2906–2912, 1993.

K. Maatje, R. M. d. Mol, and W. Rossing. Cow status monitoring (health and oestrus) using detection sensors. *Computers and Electronics in Agriculture*, 16(3):245–254, 1997.

R. M. d. Mol and W. E. Woldt. Application of fuzzy logic in automated cow status monitoring. *Journal of Dairy Science*, 84(2):400–410, 2001.

R. M. d. Mol, G. H. Kroeze, J. M. F. H. Achten, K. Maatje, and W. Rossing. Results of a multivariate approach to automated oestrus and mastitis detection. *Livestock Production Science*, 48(3):219–227, 1997.

R. M. d. Mol, A. Keen, G. H. Kroeze, and J. M. F. H. Achten. Description of a detection model for oestrus and diseases in dairy cattle based on time series analysis combined with a kalman filter. *Computers and Electronics in Agriculture*, 22(2/3):171–185, 1999.

A. S. Moore and S. L. Spahr. Activity monitoring and an enzyme immunoassay for milk progesterone to aid in the detection of estrus. *Journal of Dairy Science*, 74(11):3857–3862, 1991.

R. L. Nebel, M. G. Dransfield, S. M. Jobst, and J. H. Bame. Automated electronic systems for the detection of oestrus and timing of ai in cattle. *Animal Reproduction Science*, 60/61:713–723, 2000.

O. Peralta, R. Pearson, and R. Nebel. Comparison of three estrus detection systems during summer in a large commercial dairy herd. *Animal Reproduction Science*, 87(1-2):59–72, 2005. ISSN 03784320.

J. B. Roelofs, F. J. C. M. v. Eerdenburg, N. M. Soede, and B. Kemp. Pedometer readings for estrous detection and as predictor for time of ovulation in dairy cattle. *Theriogenology*, 64(8):1690–1703, 2005.

D. Schlünsen, H. Roth, H. Schön, W. Paul, and H. Speckmann. Automatic health and oestrus control in dairy husbandry through computer aided systems. *Journal of Agricultural Engineering Research*, 38(4):263–279, 1987. ISSN 00218634.

Oestrus Detection in Dairy Cows using Automata-Based Modelling and Diagnosis[1]

Jónsson, R., Caponetti, F., Blanke M. and Poulsen N. K.

Abstract

This paper addresses detection of oestrus in dairy cows using automata-based modelling and diagnosis. Measuring lying/standing behaviour of the cows by a sensor attached to the cows hindleg, lying/standing behaviour is modelled as a stochastic automaton. The paper introduces a cow's lying-balance as a biologically inspired quantity describing how much the cow has been resting for a preceding period. A dynamic lying-balance model is identified from real data and the lying balance is used as input, together with lying/standing sensor measurements. Using different automata models for oestrus and non-oestrus conditions, with state transition probability densities identified from observations, diagnosis theory for stochastic automata is employed to obtain diagnoses of oestrus. The oestrus cases are detected using consistency based diagnosis on real data. *Copyright IFAC 2009*

B.1 Introduction

Automatic detection of deviant behaviour amongst dairy cows is a task of rapidly growing interest in the farming field. The main focus in this perspective is to detect deviant behaviour caused by oestrus or some kind of disease. An early detection of a cow in oestrus or a cow suffering from a disease can save the farmer from a loss in production and the animal from a prolonged period of pain/uneasiness. [1]

Several studies have been conducted on the subject of automatic oestrus detection in dairy cows. Many authors, e.g. Moore and Spahr [1991], Liu and Spahr [1993] and Roelofs et al. [2005], have used simple statistical tests where a mean of recent activity was compared to antecedent values of the mean of activity. Analysis of time series were performed where parameters were updated by means of a Kalman filter in Maatje et al. [1997], Mol et al. [1997] and Mol et al. [1999]. Further, Eradus et al. [1999], Mol and Woldt [2001] and Firk et al. [2003] showed detection of oestrus by Fuzzy logic methods. Derivation of a generalised likelihood ratio test for detecting oestrus was the subject in Jonsson et al. [2008].

Methods of automated oestrus detection were reviewed by Eradus and Jansen [1999], Nebel et al. [2000] and Firk et al. [2002]. Comparison of commercial systems was done by Cavalieri et al. [2003] and Peralta et al. [2005]. A new device for detecting oestrus by means of measurements of activity and lying standing behaviour was introduced by Brehme et al. [2008].

This paper investigates the feasibility of using discrete event models to describe the cows' behaviour and diagnose reasons to deviant behaviour using methods from diagnosis of stochastic automata.

An important class of discrete event models is the automaton (Cassandras and Lafortune [2008]). The automata are useful in describing systems where the inputs, states and reactions can be described by discrete values. By modelling such a system in faulty and non-faulty modes change in the systems behaviour can be detected by checking the consistency between the model and the actual behaviour. Lack of consistency is a sign of a change in behaviour (Blanke et al. [2006]).

This study investigates data from a lying/standing sensor and proposes models and algorithms for detecting oestrus in dairy cows using stochastic automata theory. The paper describes investigations of data properties with the overall

---

goal to identify deviations in data caused by oestrus behaviour. Knowledge gained about the relation between oestrus and observed lying time is then exploited in order to construct discrete event models for detecting oestrus. Deviations in the lying behaviour are identified as deviations in the lying balance. The lying balance is a quantity suggested in this paper for observing the cows biological need to lie down.

B.2   Methods

One way of describing the cows lying/standing behaviour is to describe it with a discrete-event model, e.g. an automaton.

The cows' lying behaviour can be described by observing their lying pattern with respect to the time spent lying during the preceding period. An automaton that models this property is the stochastic lying-balance automaton. The derivation of the lying-balance and the automata for normal and oestrus behaviour are described in the following.

The discrete event model for the lying behaviour is a two state stochastic automaton with an input consisting of the observed lying/standing status and an output which is the cows lying behaviour. The lying behaviour is referred to as the lying-balance. The lying-balance is a quantity that describes the cows need to rest and is increasing when the cow is lying and decreasing when the cow is standing or walking. Hence a low lying-balance is a sign of a need to rest while a large lying-balance means that the cow should not have an urge to rest for a while.

The method for diagnosing oestrus from lying-balance consists of a model for calculating the lying balance and automata for describing the lying-behaviour under the two scenarios: normal and oestrus. The lying-balance is calculated from observations of the lying/standing status and oestrus is diagnosed by checking the consistency of the observed behaviour between the models of normal and oestrus behaviour in terms of lying-balance. An illustration of the lying-balance model and the lying-balance automata for diagnosis of oestrus is shown in Figure B.1. The section begins with the derivation of the model for calculation of the lying-balance and ends with derivation of the lying-balance automata.
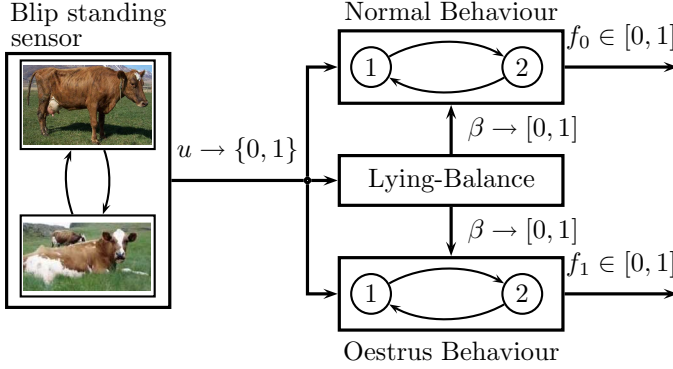
Figure B.1: A block diagram of the model.

B.2.1 Modelling the Lying-Balance

As described above, the lying-balance is a quantity that should describe the cow's need to rest. This is not easy to model from lying/standing observations as the relation between each hour resting and the cow's actual resting status is not well established.

The lying-balance is in this study modelled as a *1st order* model where the first hour of lying or standing contributes considerably more than the last hour and where the value converges to a finite value. The lying-balance model is derived below.

The estimated lying-balance is denoted $\hat{\beta}$ and is at sample k found as.

$$
\hat{\beta}_k = \begin{cases}
\beta_{max} \times \left(1 - \exp\left(-\dfrac{(\kappa + k - k_{shift})\, t_s}{\hat{\tau}_{lie_\kappa}} \right) \right) \\
\quad \text{if } y_k = 0 \\[2mm]
\beta_{max} \times \exp\left(-\dfrac{(\kappa + k - k_{shift})\, t_s}{\hat{\tau}_{stand_\kappa}} \right) \\
\quad \text{if } y_k = 1
\end{cases}
\tag{1}
$$

where β_{max} is the *maximum* value that the resting balance can have, $\beta_{max} = 1$. t_s is the sample time, y_k is the observed lying/standing status $\{lying, standing\} \rightarrow \{0, 1\}$ at sample k, $\hat{\tau}_{lie_\kappa}$ is the time constant of the growing function of the lying periods and $\hat{\tau}_{stand_\kappa}$ is the time constant of the diminishing function of the standing periods. k_{shift} is the sample number where the observations shift from one state to another, i.e. where the lying balance goes from increasing to decreasing

or vice versa, and κ is a sample value that sets the start value of the exponential function corresponding to the value of the lying balance at the sample where the observations shift from one state to another.

Both time constants are found from the recursive estimation of the lying time each 24 $hours$. Assuming that the cow has used 99% of its daily resting time $(1 - e^{-5\tau/\tau} = 0.99)$ at time of the estimated lying time each 24 $hours$ the two time constants are found as

$$
\hat{\tau}_{lie_\kappa} = \frac{\hat{d}_{k_{shift}}}{5t_s}
$$

$$
\hat{\tau}_{stand_\kappa} = \frac{24 \times 3600 - \hat{d}_{k_{shift}}}{5t_s}
$$

$$(2)$$

where $\hat{d}_{k_{shift}}$ is the value of the recursive estimation of the mean value of the lying time for each 24 $hours$ at sample k_{shift}.

The recursive mean value of the lying time for each 24 $hours$ is estimated as

$$
\hat{d}_k = \hat{d}_{k-1} + \frac{1}{T_k} \left(\frac{m_{24}}{24 \times 3600 \times \frac{1}{t_s}} - \hat{d}_{k-1} \right)
$$

$$
T_k = \lambda T_{k-1} + 1
$$

$$(3)$$

where m_{24} is the number of samples lying for the preceding 24 $hours$ and λ is the forgetting factor, which is chosen as $\lambda = 0.99$.

The sample value κ is found as

$$
\kappa =
\begin{cases}
\log \left(\dfrac{1}{1 - \frac{\beta_{k_{shift}}}{\beta_{max}}} \right) \dfrac{\hat{\tau}_{lie_\kappa}}{t_s} & \text{if } y_k = 0 \\[4mm]
\log \left(\dfrac{\beta_{max}}{\beta_{k_{shift}}} \right) \dfrac{\hat{\tau}_{stand_\kappa}}{t_s} & \text{if } y_k = 1
\end{cases}
$$

$$(4)$$

The estimation of the initial value β_0, which clearly depends on the cows' lying behaviour during the preceding period is found as

$$
\hat{\beta}_0 = \beta_{min} + \frac{m_d}{\hat{d}} \left(\beta_{max} - \beta_{min} \right)
$$

$$(5)$$

where m_d is the time spent lying during the preceding period $\hat{d}$.

B.2.2   Stochastic Automata

Since the "system" at hand, the cow, is biological, a deterministic or a non-deterministic automaton alone will not provide the necessary flexibility to cope with the complexity of behavioural patterns of live creatures with a wide variation between cows. A stochastic automaton extends the concept of the non-deterministic discrete-event systems in such a way that the frequency of the occurrence of the different events can be addressed. The model used for describing the lying/standing behaviour of the cow is a stochastic automaton. The stochastic automaton used is written in the same way as in Blanke et al. [2006] with discrete input, state and output which are denoted by v, z and w. Their discrete value sets are enumerated $v \in \mathcal{N}_v = \{1, 2, \ldots, M\}$, $z \in \mathcal{N}_z = \{1, 2, \ldots, N\}$, and $w \in \mathcal{N}_w = \{1, 2, \ldots, R\}$. Where M, N and R are finite values. The stochastic automaton is described by the 6-tuple:

$$\mathcal{S} = \langle \mathcal{N}_z, \mathcal{N}_v, \mathcal{N}_w, L, Prob(z(0)) \rangle \tag{6}$$

where $Prob(z(0))$ is the initial state probability distribution.

The stochastic automaton behaviour is described by its behavioural relation L.

$$L : \mathcal{N}_z \times \mathcal{N}_w \times \mathcal{N}_z \times \mathcal{N}_v \to [0, 1] \tag{7}$$

that represents the generation law governing the stochastic Markov process that lies behind the automaton.

$$L\left(z', w, z, v\right) = Prob(z_p(k+1) = z', w_p(k) = w | \\ z_p(k) = z, v_p(k) = v) \tag{8}$$

The discrete parameters v and w are in this study used to include the observed lying/standing status and the calculated lying balance in the models. The observed lying standing status is thus included by v and mapped into the discrete value set $\{lying, standing\} \to \{1, 2\}$. The estimated lying-balance is described by w and mapped into the discrete value set $\{VL, L, M, H\} \to \{1, 2, 3, 4\}$. The mapping of the lying-balance from $\hat{\beta} \to [0, 1]$ to the discrete value set $\mathcal{N}_w = \{1, 2, 3, 4\}$ is given by

$$w = \begin{cases} 1 & \text{if } 0 \leq \hat{\beta}_k \leq 0.2 \\ 2 & \text{if } 0.2 < \hat{\beta}_k \leq 0.4 \\ 3 & \text{if } 0.4 < \hat{\beta}_k \leq 0.7 \\ 4 & \text{if } 0.7 < \hat{\beta}_k \leq 1 \end{cases} \tag{9}$$

The discretisation intervals are shown in Figure B.5 and the associated automaton model is shown in Figure B.2.
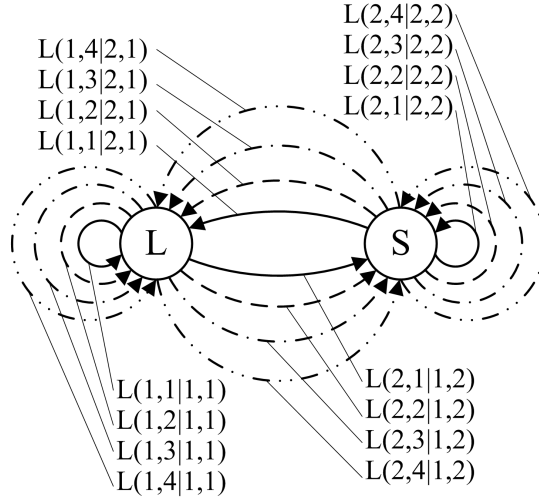
Figure B.2: Automata for the lying balance where $L(z', w|z, v) = Prob(z', w|z, v)$. Equal line style means equal w.

B.2.3 Diagnosis

For identifying faults or abnormal behaviour in a system the system is diagnosed. The diagnosis method is based on modelling the system with automata and checking the consistency between the automata and the actual behaviour. Lack of consistency is an indication of a change in the behaviour. An isolation of a certain behavioural scenario can be done by also modelling the specific behaviour to be detected and again checking the consistency between the model describing the deviant behaviour and the actual behaviour. Thus if the observed behaviour is not consistent with the normal case and at the same time there exists consistency with the model of the specific deviant behaviour the specific behaviour is isolated.

B.2.3.1 Stochastic Automata for Diagnosis

In order to describe the behaviour of the stochastic automata under the influence of behavioural scenarios, the scenario $f(k)$ is introduced as an additional input. The fault extends the notion of an automaton that now becomes

$$\mathcal{S} = \langle \mathcal{N}_z, \mathcal{N}_v, \mathcal{N}_f, \mathcal{N}_w, L, Prob(z(0)) \rangle \tag{10}$$

with $\mathcal{N}_f$ denoting the set of possible behavioural scenarios.

The behavioural scenario is assumed to be an output of another stochastic automaton:

$$\mathcal{S}_f = \langle \mathcal{N}_f, \mathcal{G}_f, Prob(f(0)) \rangle \tag{11}$$

where G_f is the state transition relation, which describes the conditional probability that the behavioural scenario changes from f to f' within a time step.

$$G_f : \mathcal{N}_f \times \mathcal{N}_f \to [0, 1] \tag{12}$$

$$G_f(f'|f) = Prob\left(f_p(k+1) = f'|f_p(k) = f\right) \tag{13}$$

The main aim is to ask to the model whether a given I/O pair is consistent with the automaton connected to the normal behaving cow or to the oestrus one. It is assumed that the discrete input changes its value simultaneously with the occurrence of an event and the discrete output is measured correspondingly.

The two behavioural scenarios that are treated in this study, i.e. normal and oestrus, which are expressed by the f parameter, are mapped into the discrete value set $\{normal, oestrus\} \to \{1, 2\}$.

B.2.3.2   Diagnosis of the Stochastic Automata

The diagnostic problem for the above described discrete event system is addressed e.g. by Blanke et al. [2006]. The algorithm on page 420 in Blanke et al. [2006] is used directly.

B.2.4   Learning

The determination of the probability of a given transition is a difficult task since not a lot of information is given. Looking at the reference Blanke et al. [2006] the abstraction algorithm is reviewed. Such algorithm is based upon an approximate evaluation of the transition frequency. Given a hand-classified dataset, it is possible to take a uniformly distributed sample and evaluate how many times each transition occurs. The simplest method uses a grid of N points distributed uniformly over the number of available measurements and determines the set of successor states z' together with the input v and output w at the same time under the behavioural scenario f. Then the number $N_{z',w,v,z,f,v}$ represent how many times a given transition is enabled. Having that information for each transition it is possible to evaluate the approximated probability by the relative

frequency as follows:

$$L\left(z', w | z, f, v\right) = \frac{N_{z',w,z,f,v}}{\displaystyle\sum_{z' \in \mathcal{N}_z} \sum_{w \in \mathcal{N}_w} N_{z',w,z,f,v}} \tag{14}$$

Feeding that probability in the L matrix with all the initial probabilities 0 there exists a risk that there may occur some null transitions. Also in Blanke et al. [2006] it is noted that using that method the completeness of the model cannot be ensured. The reason for this is given by the fact that even for a large number of samples not all state transition for all the possible couple input/output are found, hence the algorithm yields

$$L(z', w | z, v) = 0 \tag{15}$$

even if the transition $z \rightarrow z'$ is feasible for the real system. For the probability evaluation of discrete-event models of quantised systems, it is still possible to determine a complete model using a Lipschitz condition while choosing the sample points to evaluate, refer to Blanke et al. [2006] for further details. Since we are dealing with biological systems i.e. cows such kind of complete modeling is not appliable in a straight forward manner.

In this actual case the risk of acquiring a null transition depends on the number of discretisation intervals chosen as well as the interval limits (see e.g. eq. (9)). Choosing some interval limits that are either very high or very low increases the risk of acquiring null transitions as values in these intervals occur seldom. Thus in order to avoid inconsistent I/O pairs the frequency count is initialised with a one for each transition. In that way once all the transition are sampled and counted even if a certain transition is not caught by the sampling it's probability will be small compared to the others but still not zero.

B.3   Case Test

In order to assess the relevance of the methods described, the algorithms were tested on just under 6 weeks of data for cow number 702. The cow was inseminated once during the 6 weeks and later there was performed a pregnancy test with a positive result, which means that the detected oestrus case was a true oestrus case.

The section begins with a brief description of the data followed by some data inspections and ending with showing results of a test performed on the data for the cow.
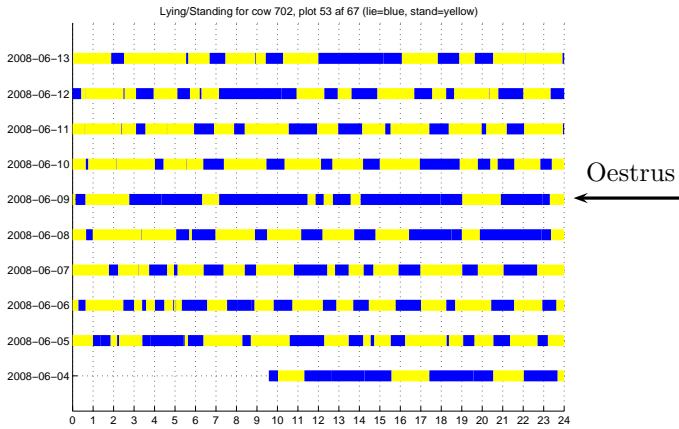
Figure B.3: An extract of the lying behaviour for cow no. 702. Each line in the plot corresponds to 24 *hours* of lying behaviour from $[0, 24[\,hours$. The lying periods are shown in blue and the standing periods in yellow. An oestrus case is indicated on June 9 year 2008, as a successful insemination was performed on that date.

B.3.1   Data

The data set used for the test contains measurements of two states namely the states standing/not standing. The data were recorded at the Danish Cattle Research Centre by means of a measuring device under development. The measuring tag is attached to the cow's hindleg and switches between the two states at an angle of $45° \pm 10°$. The observations are event sampled, i.e. each time the tag-angle passes the $45° \pm 10°$ limit and observation containing the time of the observation and the state value. The observed state value is mapped into the values $\{not\ standing, standing\} = \{0, 1\}$.

Figure B.3 shows an example of the raw data.

B.3.1.1   Oestrus period

In order to get an overview of how distinct the behavioural changes in the lying standing behaviour resulting from an oestrus plots of time series were plotted where data belonging to normal behaviour were compared with data belonging to oestrus behaviour. Data from $2008-06-08\ at\ 19.00$ to $2008-06-09\ at\ 19.00$

was categorised as belonging to oestrus behaviour while the rest of the data set was categorised as belonging to normal behaviour. The exact start and end time of the oestrus period was assessed by visually inspecting the plot in Figure B.3. The oestrus period is indicated in the time series plots with a green shaded area.

B.3.1.2 Treatment of Missing Data

As the lying/standing sensor sends a counter value for each transmission, it is possible to identify missing observations in the data set. There was a substantial amount of missing data in the lying/standing data, where there either was missing one transmission between two successful observations or there were missing days of successive observations. In the cases of one or two successive observations missing they were replaced with observations with equal space between them in between the two successful ones. In the case of more than two observations missing, the algorithm is halted and not started again until after data start to appear again.

B.3.1.3 Lying Time each 24 *hours*

The calculated lying time each 24 *hours*, m_{24}, and the recursively estimated mean, $\hat{d}_k$ are plotted in Figure B.4

When observing the plotted time spent lying over 24 *hour* in Figure B.4 one can see that the time spent lying varies a lot with a significant drop on the day of insemination.

B.3.1.4 Properties of Lying-Balance

The lying-balance was investigated with respect to distinctness under oestrus by plotting time series of the calculated lying-balance, Figure B.5.

By inspecting Figure B.5 one can see that the most obvious drop in the lying-balance happens around the insemination date on June 9.
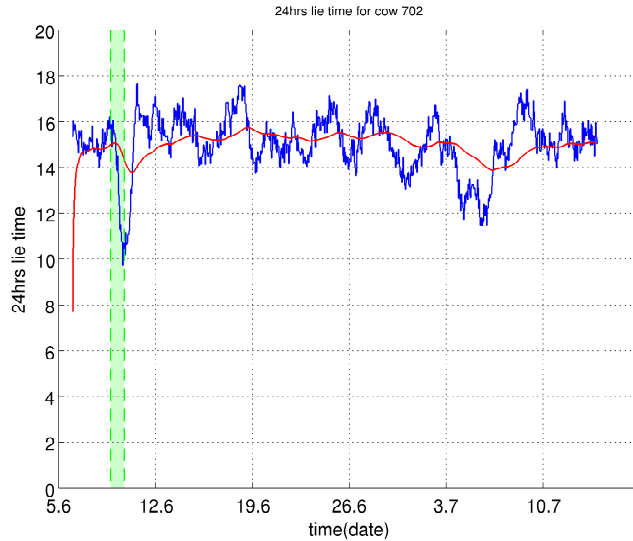
Figure B.4: Time spent lying for the last 24 hours, calculated for each hour over a period of 6 weeks. The time spent lying is plotted in blue, a recursively estimated mean of the time spent lying is plotted in red and the insemination date is shown with a green shaded area.

B.3.2 Diagnosis Test

The diagnosis algorithm was tested on the data for cow number 702 using diagnosis algorithms for the the stochastic lying-balance automata.

Transition probabilities were found using the algorithm in section B.2.4. The calculated transition probabilities for the observed are shown in Figure B.6.

The diagnosis was performed using the algorithm in section B.2.3. The results of the test performed on the calculated lying-balance and observed states are shown in Figure B.7.

As shown in Figure B.7 the oestrus case on June 9 was detected as the algorithm indicates that the observations at the time of the oestrus could not belong to the model describing the normal behaviour.
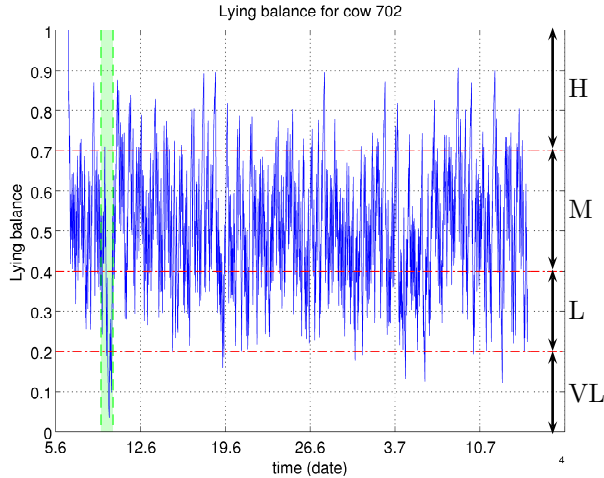
Figure B.5: Plots of *1st order* estimated lying-balance with discretisation intervals indicated in the right side.

B.4   Discussion

It was instrumental to the success of the diagnosis method presented that the lying-balance was estimated and made part of the automata input. The diagnosis would not work well until the lying-balance was introduced in the automata. The initial study included other modelling methods, including timed automata models, but these fell short in producing useful diagnoses. The lack of results when using the timed automata is due to the fact that cows' lying behaviour with respect to the duration of each lying or standing period are not significantly different under oestrus and normal behaviours. A salient feature captured in the lying-balance is a skewed distribution of the balance between time spent lying and time spent standing each 24 *hours* during the oestrus period, although a difference in duration of each lying or standing period is not evident. A means of describing the ratio between time spent lying and time spent standing was to model the cows lying-balance giving an indication of the cows need to rest or lie down at each point in time. It was therefore concluded that the lying/standing behaviour should be modelled with stochastic automata instead of timed automata.

This study raises expectations on being able to use data from lying/standing sensors to determine the reproductive status of a cow. If not as a sole trait in a detector then at least as a supplement to an algorithm that uses other traits, such as activity, as a measure on whether the cow is in oestrus or not and thereby contributing to a less error prone oestrus detection system.
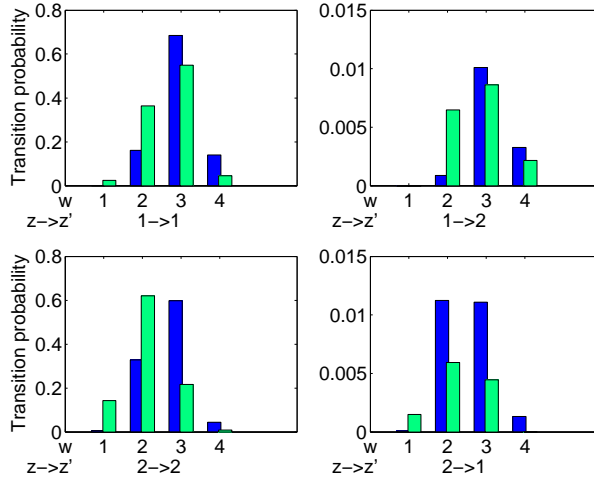
Figure B.6: Calculated transition probabilities. The transition probabilities
of the normal behaviour are shown in blue and of the oestrus
behaviour in green. For each transition $z \rightarrow z'$ the transition is
shown for each possible value of w summed over all possible input
values v.

The individual variation of behaviour is rather large between animals in a heard.
Therefore, this study, using data from one cow only, is not supporting a conclu-
sion that the method will work equally well on any cow, but it is believed that
the study will be useful when extending the results to larger sets of data and
also when lying/standing sensor data are merged with other sensor information,
e.g activity sensor data, for use in diagnosis.

B.5   Conclusion

A discrete event model was derived for detecting oestrus in dairy cows using
stochastic automata.

A biologically inspired quantity describing how much the cow has been resting
for the preceding period was derived. A discretised value of the lying balance
was used as a parameter in the stochastic automata.

A diagnosis algorithm for detecting oestrus using stochastic automata for de-
scribing the two behavioural scenarios: normal and oestrus behaviour, was im-
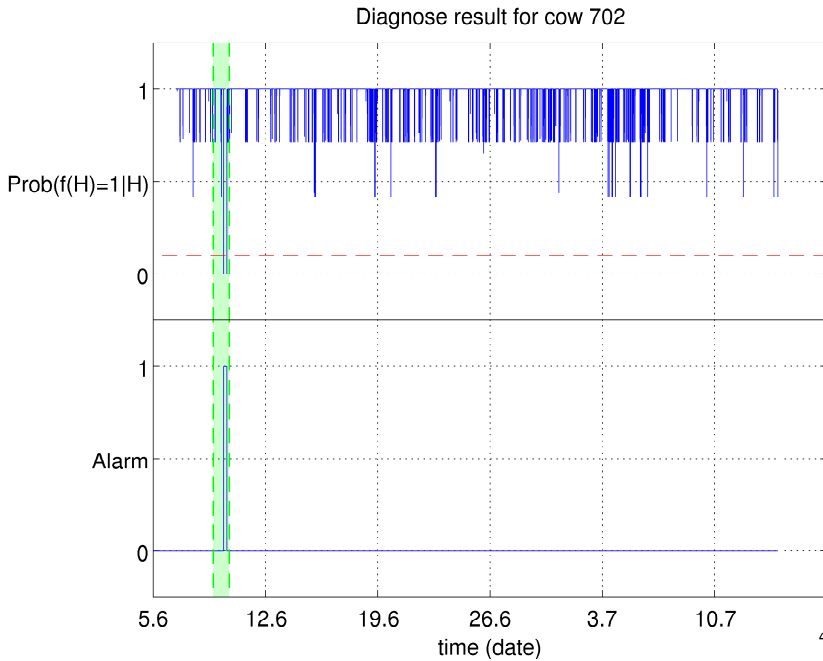
Figure B.7: Results of the diagnosis algorithm used on observations when applying the algorithm for stochastic automata.

plemented and tested on data for one cow where the oestrus case was detected without false alarms.

B.6   Acknowledgements

References

M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki. *Diagnosis and Fault-Tolerant Control*. Springer, 2 edition, 2006.

U. Brehme, U. Stollberg, R. Holz, and T. Schleusener. Alt pedometer-new sensor-aided measurement system for improvement in oestrus detection. *Computers and Electronics in Agriculture*, 62(1):73–80, 2008. ISSN 01681699.

C. Cassandras and S. Lafortune. *Introduction to Discrete Event Systems*. Springer, 2 edition, 2008.

J. Cavalieri, V. E. Eagles, M. Ryan, and K. L. MacMillan. Comparison of four methods for detection of oestrus in dairy cows with resynchronised oestrous cycles. *Australian Veterinary Journal*, 81(7):422–425, 2003.

W. J. Eradus and M. B. Jansen. Animal identification and monitoring. *Computers and Electronics in Agriculture*, 24(1/2):91–98, 1999.

W. J. Eradus, H. Scholten, and A. J. Udink-ten Cate. Oestrus detection in dairy cattle using a fuzzy inference system. *Control applications and ergonomics in agriculture CAEA ' 98: A Proceedings volume from the IFAC Workshop, Athens, Greece, 14 17 June 1998*, 1999.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Automation of oestrus detection in dairy cows: a review. *Livestock Production Science*, 75(3):219–232, 2002.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Oestrus detection in dairy cows based on serial measurements using univariate and multivariate analysis. *Archiv fur Tierzucht*, 46(2):127–142, 2003.

R. I. Jonsson, T. Bjorgvinsson, M. Blanke, K. Poulsen, N., S. Hojsgaard, and L. Munksgaard. Oestrus detection in dairy cows using likelihood ratio tests. In *Proceedings of the 17th World Congress, The International Federation of Automatic Control, Seoul, Korea, July 6-11*, 2008.

X. Liu and S. L. Spahr. Automated electronic activity measurement for detection of estrus in dairy cattle. *Journal of Dairy Science*, 76(10):2906–2912, 1993.

K. Maatje, R. M. d. Mol, and W. Rossing. Cow status monitoring (health and oestrus) using detection sensors. *Computers and Electronics in Agriculture*, 16(3):245–254, 1997.

R. M. d. Mol and W. E. Woldt. Application of fuzzy logic in automated cow status monitoring. *Journal of Dairy Science*, 84(2):400–410, 2001.

R. M. d. Mol, G. H. Kroeze, J. M. F. H. Achten, K. Maatje, and W. Ross-ing. Results of a multivariate approach to automated oestrus and mastitis detection. *Livestock Production Science*, 48(3):219–227, 1997.

R. M. d. Mol, A. Keen, G. H. Kroeze, and J. M. F. H. Achten. Description of a detection model for oestrus and diseases in dairy cattle based on time series analysis combined with a kalman filter. *Computers and Electronics in Agriculture*, 22(2/3):171–185, 1999.

A. S. Moore and S. L. Spahr. Activity monitoring and an enzyme immunoassay for milk progesterone to aid in the detection of estrus. *Journal of Dairy Science*, 74(11):3857–3862, 1991.

R. L. Nebel, M. G. Dransfield, S. M. Jobst, and J. H. Bame. Automated elec-tronic systems for the detection of oestrus and timing of ai in cattle. *Animal Reproduction Science*, 60/61:713–723, 2000.

O. A. Peralta, R. E. Pearson, and R. L. Nebel. Comparison of three estrus detection systems during summer in a large commercial dairy herd. *Animal Reproduction Science*, 87(1-2):59–72, 2005. ISSN 03784320.

J. B. Roelofs, F. J. C. M. v. Eerdenburg, N. M. Soede, and B. Kemp. Pedometer readings for estrous detection and as predictor for time of ovulation in dairy cattle. *Theriogenology*, 64(8):1690–1703, 2005.

Combination of activity and lying/standing data for detection of oestrous in cows[1]

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Abstract

The objective of this study is to develop an algorithm for detecting oestrus in dairy cows from measurements of activity and duration of lying/standing periods. Each cows activity is measured by a sensor attached to the neck that returns an activity index for each hour. Duration of lying is measured by a sensor attached to the hind leg of the cow. Activity and lying/standing behaviour are modelled as a discrete event system, constructed using automata theory. In an attempt to estimate a biologically relevant lying balance, a lying balance indicator is constructed and is influencing transition probabilities in the stochastic automata. The cows lying-balance indicates how much the cow has been resting during the immediately past period, and the balance express to the automata, the tendency of the cow to continue resting or not. Automata for describing the two scenarios; normal and oestrus are designed and results

of decision algorithms are presented for Oestrus detection. Detection based on the lying balance indicator and the two sets of measured information are demonstrated to increase the detection sensitivity to 100% for a set of 10 cows.

C.1 Introduction

Automatic detection of deviant behaviour in dairy cows is a task of growing interest in the modern farming. A main focus in this perspective is to detect deviant behaviour caused by oestrus, reduced feed intake or diseases. Detection of cows in oestrus or early detection of cows suffering from a disease can save the farmer from economic loss and the animal from a prolonged periods of pain/discomfort. Several studies have been conducted on the subject of automatic oestrus detection in dairy cows based on recording of activity. Analysis of time series where parameters were updated by means of a Kalman filter was performed by Mol et al. [1997], Mol et al. [1999] and Maatje et al. [1997]. Further, Mol and Woldt [2001], Eradus et al. [1999] and Firk et al. [2003] detected oestrus by Fuzzy logic methods. Derivation of a generalised likelihood ratio test for detecting oestrus was performed by Jónsson et al. [2008]. A device for detecting oestrus by means of measurements of activity and lying/standing behaviour was introduced by Brehme et al. [2008]. Methods of automated oestrus detection were reviewed by Eradus and Jansen [1999], Firk et al. [2002] and Nebel et al. [2000]. In all three articles the authors' objective was to cover the most significant methods and results in oestrus detection at each time. This paper investigates the feasibility of combining measurements of cows activity together with measurements of lying/standing behaviour in order to achieve improved detection results. Additionally the paper investigates the feasibility of using discrete event models to describe the cows behaviour and diagnose reasons to deviant behaviour using methods from diagnosis of stochastic automata. An important class of discrete event models is the automaton (see e.g. Cassandras and Lafortune [2008]). The automata are useful in describing systems where the inputs, states and reactions can be described by discrete values. By modelling such a system in faulty and non-faulty modes a change in the systems behaviour can be detected by checking the consistency between the model and the actual behaviour. Lack of consistency is a sign of a change in behaviour (Blanke et al. [2006]). This study investigates data from an activity sensor and a lying/standing sensor and proposes models and algorithms for detecting oestrus in dairy cows using stochastic automata theory. The paper describes methods for identifying deviations in data caused by oestrus behaviour. Deviations in activity behaviour are identified as deviations in discretized activity measurements while deviations in the lying behaviour are identified as deviations in the lying balance. The lying balance is a quantity suggested for observing the cows biological need to lie down.

C.2   Stochastic Automata

A stochastic automaton is an extension of the concept of non-deterministic discrete-event systems in such a way that the frequency of the occurrence of the different events can be addressed. The behaviour of the biological object, the dairy cow, could never be fully captured in such models but our hypothesis is that one could attempt to model some overall behaviours in this way. In this context, a model describing the activity level and lying/standing behaviour of the cow is desired. A stochastic automaton (chapter 8 in Blanke et al. [2006]) has discrete input, state and output, denoted by v, z and w. Two behavioural scenarios, normal behaviour and oestrus behaviour, are introduced as an input to the automaton and are denoted by f. The values of v, z, w and f, are enumerated as $v \in \mathcal{N}_v = \{1, 2, \ldots, M\}$, $z \in \mathcal{N}_z = \{1, 2, \ldots, N\}$, $w \in \mathcal{N}_w = \{1, 2, \ldots, R\}$, and $f \in \mathcal{N}_f = \{1, 2, \ldots, Q\}$, where M, N, R and Q are finite values. The stochastic automaton with additional parameter for describing behavioural scenario is described by the 6-tuple

$$\mathcal{S} = \langle \mathcal{N}_z, \mathcal{N}_v, \mathcal{N}_f, \mathcal{N}_w, L, Prob(z(0)) \rangle \tag{1}$$

where $\mathrm{Prob}(z(0))$ is the initial state probability distribution and L is the behavioural relation, given as

$$L : \mathcal{N}_z \times \mathcal{N}_v \times \mathcal{N}_z \times \mathcal{N}_f \times \mathcal{N}_w \to [0, 1]$$
$$L\left(z', w | z, f, v\right) = Prob(z_p(k+1) = z', w_p(k) = w | z_p(k) = z, f_p(k) = f, v_p(k) = v) \tag{2}$$

where z_p, w_p, v_p and f_p symbolise the stochastic variables and where k is the sample number. In order to express the transition relation between the possible scenarios, normal and oestrus respectively, a fault model is introduced

$$\mathcal{S} = \langle \mathcal{N}_f, G_f, Prob(f(0)) \rangle \tag{3}$$

where G_f is the transition relation that in our case describes the conditional probability that the behavioural scenario changes in one time step

$$G_f : \mathcal{N}_f \times \mathcal{N}_f \to [0, 1]$$
$$G_f(f'|f) = Prob\left(f_p(k+1) = f' | f_p(k-1) = f\right) \tag{4}$$

A combination of the fault model with the stochastic automation is then

$$\tilde{\mathcal{S}} = \left\langle \mathcal{N}_{\tilde{z}}, \mathcal{N}_v, \mathcal{N}_w, \tilde{L}, Prob(\tilde{z}(0)) \right\rangle \tag{5}$$

where. The transition relation from time k to time $k+1$ is then found as

$$\tilde{L}\left(z', w | z, f, v\right) = L\left(z', w | z, f, v\right) \cdot G_f(f'|f) \tag{6}$$

Identifying the behaviour as belonging to one of the two categories: Oestrus or non-oestrus, the system is said to be diagnosed. The diagnosis method is based on checking the consistency between the automata models and actual behaviour as observed by available sensors. Lack of consistency with one model is a sign of changed behaviour. Fault isolation can be done by also modelling the specific behaviour to be detected and again checking the consistency between the model describing the deviant behaviour and the actual behaviour. Thus if the observed behaviour is not consistent with the normal case and at the same time there exists consistency with the model of the specific deviant behaviour the specific behaviour is isolated.

C.2.1 Modelling activity with stochastic automata

The cows activity is modelled as a stochastic automaton. An automaton has two observable parameters, namely the input v and the output w; however the input is not used. The measured activity is discretised into a predefined number of levels and each activity level represents a state in the activity model. The output is the discretised activity. Denoting the activity with x the mapping of the activity measurements to the discrete value set $\mathcal{N}_w = \{1, 2, 3, 4\}$ is given by

$$
w = \begin{cases}
1 & \text{if } 0 \leq x \leq 30 \\
2 & \text{if } 30 < x \leq 40 \\
3 & \text{if } 40 < x \leq 130 \\
4 & \text{if } 130 < x
\end{cases}
\tag{7}
$$

The set of states is the same as the set of outputs, hence $\mathcal{N}_z = \mathcal{N}_w$. Each transition (edge) in the automaton assigns the same output value as the value of the next state z', i.e. if the automaton is moving towards state $z' = 1$ it assigns the output value $w = 1$. An example of a four state stochastic automaton is shown in Figure C.1.

The transition probabilities of the two automata models for normal behaviour and for oestrus behaviour are assessed by calculating

$$
L(z', w | z, f, v) = \frac{N_{z',w,z,f,v}}{\sum_{z' \in \mathcal{N}_z} \sum_{w \in \mathcal{N}_w} N_{z',w,z,f,v}}
\tag{8}
$$

where $N_{z',w,z,f,v}$ is the number of observations for the transition from z to z' at a certain value of w, f, and v. Figure C.2 displays the number of transitions from the present state towards the next state as well as the total number of transitions from the present state. This means that each of the first four bars in the plot is a numerator and that the last bar is the denominator. The left graph
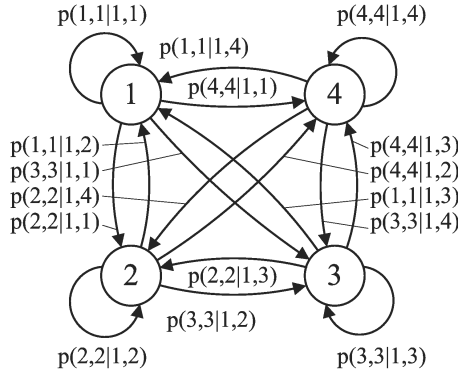
Figure C.1: Example of a four state automaton

in Figure C.2 shows observed transitions from state $z = 2$ while the right graph shows observed number of transitions from state $z = 3$. Although Figure C.2 only shows transitions from $z = 2$ and $z = 3$ all transitions are allowed in the model. Transition probabilities for the model describing the normal behaviour are calculated using the observed data from the last 18 days, at each sample. Transition probabilities for the model describing the oestrus behaviour are found differently for the activity data and the lying/standing data. The model training on the data set is described in section C.3.2.

The diagnostic problem for the above described discrete event system is addressed e.g. by Blanke et al. [2006]. The algorithm on page 420 in Blanke et al. [2006] is used directly.

C.2.2 Modelling lying behaviour with stochastic automata

The cows lying behaviour can be described by observing their lying pattern with respect to the time spent lying during the preceding period. An automaton that models this is a stochastic lying-balance automaton and is described in the following. The discrete event model for the lying behaviour is a two state stochastic automaton with an input consisting of the observed lying/standing status and an output which is the cows lying behaviour. The lying behaviour is referred to as the lying-balance. The lying-balance is a quantity that describes the cows need to rest and is increasing when the cow is lying and decreasing when the cow is standing or walking. Hence a low lying-balance is a sign of a need to rest while a large lying-balance means that the cow should not have an urge to rest for a while. The method for diagnosing oestrus from lying-balance

(a) $z = 2$ (b) $z = 3$
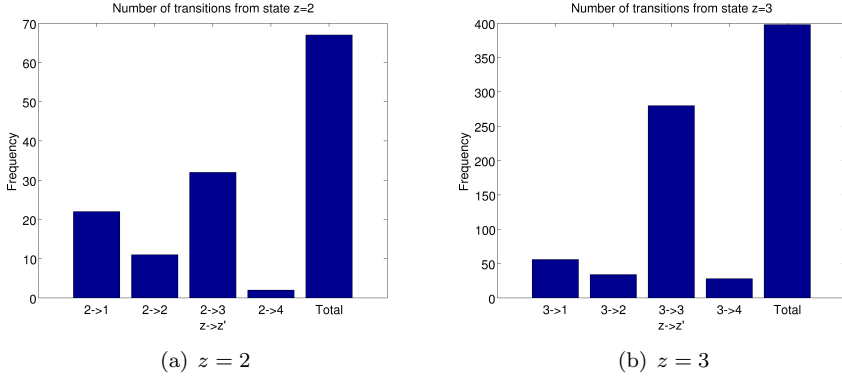
Figure C.2: Observed transition frequency for the cows activity from states $z = 2$ and $z = 3$ under oestrus for 50 cows.

consists of a model for the lying balance and automata for describing the lying-behaviour under the two scenarios; normal and oestrus. The lying-balance is in this study modelled as a 1st order model where the first hour of lying or standing contributes considerably more than the last hour and where the value converges to a finite value. The lying-balance model is derived below. The lying-balance is denoted β and is at sample k found as

$$
\hat{\beta}_k =
\begin{cases}
\beta_{max} \times \left(1 - \exp\left(-\dfrac{(\kappa + k - k_{shift})\, t_s}{\hat{\tau}_{lie_\kappa}} \right) \right) \\
\quad \text{if } z_k = 0 \\
\beta_{max} \times \exp\left(-\dfrac{(\kappa + k - k_{shift})\, t_s}{\hat{\tau}_{stand_\kappa}} \right) \\
\quad \text{if } z_k = 1
\end{cases}
\tag{9}
$$

where β_{max} is the maximum and is in this study set to 1. The sampling period is t_s and z_k is the observed lying/standing status $\{lying, standing\} \rightarrow \{0, 1\}$ at sample k, $\hat{\tau}_{lie_\kappa}$ is the time constant of the growing function of the lying periods and $\hat{\tau}_{stand_\kappa}$ is the time constant of the diminishing function of the standing periods. k_{shift} is the last sample number where the observations shift from one state to another, i.e. where the lying balance goes from increasing to decreasing or vice versa, and κ is a sample value that sets the start value of the exponential function corresponding to the value of the lying balance at the sample where the observations shift from one state to another. The time constants $\hat{\tau}_{lie_\kappa}$ and $\hat{\tau}_{stand_\kappa}$ are found using recursive estimation of the lying time each 24 *hours*. Assuming that the cow has used 99% of it is daily resting time $\left(1 - e^{-5\tau/\tau} = 0.99\right)$ at time

of the estimated lying time each 24 *hours* the two time constants are found as

$$\hat{\tau}_{lie_\kappa} = \frac{\hat{d}_{k_{shift}}}{5t_s} \qquad\qquad \hat{\tau}_{stand_\kappa} = \frac{24 \times 3600 - \hat{d}_{k_{shift}}}{5t_s} \tag{10}$$

where $\hat{d}_{k_{shift}}$ is the value of a recursive estimation of the mean value of the lying time for each 24 *hours* at sample H_{shift}. The recursive mean value of the lying time for each 24 *hours* is estimated as

$$\hat{d}_k = \hat{d}_{k-1} + \frac{1}{T_k}\left(\frac{m_{24}}{24 \times 3600 \times \frac{1}{t_s}} - \hat{d}_{k-1}\right) \qquad T_k = \lambda T_{k-1} + 1 \tag{11}$$

where m_{24} is the number of samples lying for the preceding 24 *hours* and λ is a forgetting factor which in this study is selected as 0.99. The sample value κ is found as

$$\kappa = \begin{cases} \log\left(\dfrac{1}{1 - \frac{\beta_{k_{shift}}}{\beta_{max}}}\right)\dfrac{\hat{\tau}_{lie_\kappa}}{t_s} & \text{if } z_k = 0 \\[2.5ex] \log\left(\dfrac{\beta_{max}}{\beta_{k_{shift}}}\right)\dfrac{\hat{\tau}_{stand_\kappa}}{t_s} & \text{if } z_k = 1 \end{cases} \tag{12}$$

Estimation of the initial value β_0, which depends on the cows lying behaviour during the preceding period, is computed as

$$\hat{\beta}_0 = \beta_{min} + \frac{m_d}{\hat{d}}\left(\beta_{max} - \beta_{min}\right) \tag{13}$$

where m_d is the time spent lying during the preceding period $\hat{d}$. The discrete parameters v and w are used to include the observed lying/standing status and the calculated lying balance in the models. The observed lying standing status is thus included by v and mapped into the discrete value set $\{lying, standing\} \rightarrow \{0, 1\}$. The estimated lying-balance is described by w and mapped into the discrete value set $\{VL, M\} \rightarrow \{1, 2\}$. The mapping of the lying-balance from $\hat{\beta} \rightarrow [0, 1]$ to the discrete value set $\mathcal{N}_w = \{1, 2\}$ is chosen as

$$w = \begin{cases} 1 & \text{if } 0 \le \hat{\beta}_k \le 0.05 \\ 2 & \text{if } 0.05 < \hat{\beta}_k \le 1 \end{cases} \tag{14}$$

The transition probabilities for the lying-balance automata are found in the same way as for the activity automata using equation (7).

C.2.3 Combination of two Detectors

The combination of the detection results in one detector is done as follows. As neither the activity detector nor the lying-balance detector is particularly

sensitive, the result is that if either detector detects a possible oestrus, an alarm
is issued.

C.3   Test Results

In order to assess the relevance of the methods described, the algorithms were
tested on approximately 4 weeks of data from 10 cows. Each of the 10 cows were
inseminated once in the middle of the 4 weeks period and later gave a positive
result in a pregnancy test.

C.3.1   Data Set

The data set used for the study consists of measurements of activity and lying
behaviour on cows in a loose housing system with robots at the Danish Cattle
Research Centre. The activity was measured by means of commercial activity
tags placed on the cows neck. The activity tags are developed by DeLaval and
are of the type ALPRO®. The activity tags return an activity measurement
which consists of an activity index for each hour. The data set for the lying
behaviour contains measurements of two states namely the states standing/not
standing. The data were recorded by means of a measuring device under de-
velopment. The measuring tag is attached to the cows hind leg and switches
between the two states at an angle of $45° \pm 10°$. The observations are event
sampled, i.e. each time the tag-angle passes the $45° \pm 10°$ limit and observation
containing the time of the observation and the state value. The observed state
value is mapped into the values $\{not\ standing, standing\} = \{0, 1\}$. Two weeks
of data before and after insemination from 10 cows which were tested positive
in a pregnancy test were used in this study.

C.3.2   Training of oestrus models and missing data

The transition probabilities for the models describing the oestrus behaviour
are like that of the normal models found using equation (7). The transition
probabilities for the model describing the oestrus behaviour of the activity data
were trained using activity data from 50 cows on the day of insemination 9
months before calving. None of the oestrus cases in the activity training data
set was identical with any of the 10 oestrus cases tested in this study. Due to
lack of oestrus data in the lying/standing data set, the transition probabilities

for the model describing the oestrus behaviour of the lying/standing data were calculated using data from the data set used in the study. The model describing the oestrus behaviour of the lying/standing data was therefore trained using data from 10 oestrus cases. As the lying/standing sensor sends a counter value for each transmission, it is possible to identify missing observations in the data set. There was a substantial amount of missing data in the lying/standing data, where there either was missing 1 transmission between 2 successful observations or there were missing days of successive observations. Periods where there were days of missing observations were partly due to occasional halting of the data server in connection with changes on other systems that are treated by the same server. In the cases of 1 or 2 successive observations missing they were replaced with observations with equal space between them in between the 2 successful ones. In the case of more than 2 observations missing, the algorithm is halted and not started again until 12 hours after data start to appear again.

C.3.3   Diagnosis Test

The diagnosis algorithm was tested on the data for the 10 cows using the diagnosis algorithm on page 420 in Blanke et al. [2006] on the automata models derived in section C.2. The detection results are presented as sensitivity and specificity which are calculated as

$$Sens. = \frac{tp}{tp + fn}, \qquad Spec. = \frac{tn - tp}{tn} \qquad (15)$$

where tp is number of successful detections, fn number of missed oestrus cases, tn number of days outside of oestrus period without a detection and f_p number of days where a detection is issued out side of the oestrus period. The detection results are listed in Table C.1 and an example of data for activity and lying balances as well as the combined diagnosis for cow no. 702 are shown in Figure C.3.

When observing the results in Table C.1 one can see that by combining the results of the two detectors all 10 oestrus cases are detected on the cost of 3 false alarms.

C.4   Conclusion

A discrete event model was derived for detecting oestrus in dairy cows from measurements of activity and lying/standing behaviour using stochastic automata

Table C.1: Detection results for detecting oestrus in 10 cows using measurements of activity and lying behaviour.

Cow No.	Activity		Lying-bal.		Combined	
	Sens.[%]	Spec.[%]	Sens.[%]	Spec.[%]	Sens.[%]	Spec.[%]
362	100	100	0	92	100	92
480	100	100	0	100	100	100
524	100	100	0	100	100	100
568	0	100	100	100	100	100
702	100	100	100	100	100	100
747	0	100	100	100	100	100
757	100	100	0	96	100	96
759	0	100	100	100	100	100
774	0	100	100	100	100	100
816	100	100	0	100	100	100
Total	60	100	50	99	**100**	**99**

theory. As a salient feature, a lying balance was introduced, a biologically inspired quantity describing how much the cow has been resting for the preceding period. This biological balance influenced the transition probabilities between states in the stochastic automata. Cows were found not to have any distinct pattern in lying/standing behaviour regarding the length of each lying and standing period, but use of the lying balance as input to the stochastic automata significantly enhanced the detection quality for lying behaviour under oestrus. Combining with detection based on cows activity provided a significant increase in detection sensitivity. However, further studies with a larger number of cows is needed, and enough data so that training and estimation of detection sensitivity can be done on different dataset. An assessment of the time of each detection with respect to the actual time for onset of oestrus was not dealt with in this study but is rather a subject of further study.

C.5   Acknowledgements
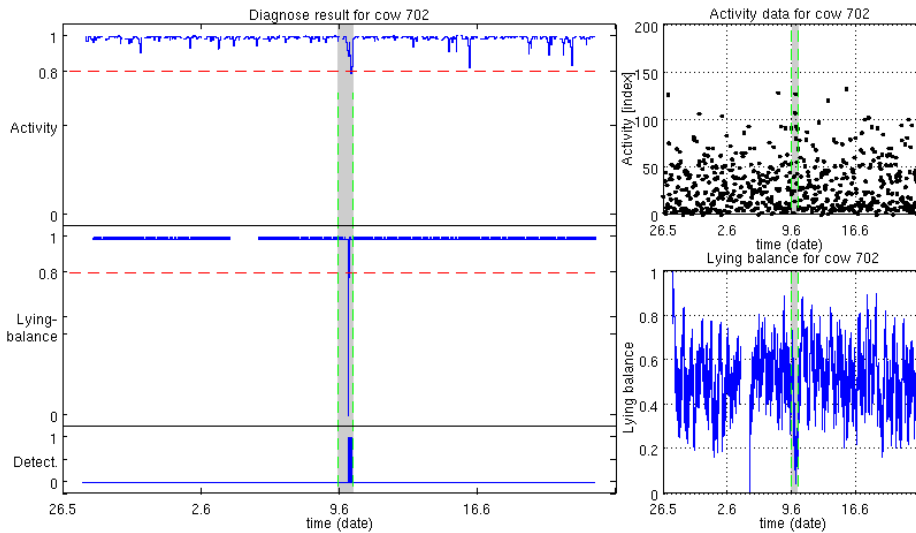
Figure C.3: *Left:* Combined diagnosis results for cow no. 702. The part labelled "Activity" shows the probability that the cows behaviour in terms of activity can be classified as normal behaviour, the part labelled "Lying-balance" shows the probability that the cows behaviour in terms of lying-balance can be classified as normal behaviour and the part labelled "Detect." shows the combined detection result. The detection threshold is shown with a dashed horizontal line and the oestrus period is shown with a shaded area. *Right top:* Activity index for cow no. 702. The oestrus period is shown with a shaded area. *Right bottom:* Lying-balance for cow no. 702. The lying balance is a dimensionless quantity in the range [0,1] where 1 indicates a minor need to lie down and 0 indicates an urgent need to lie down. The oestrus period is shown with a shaded area.

References

M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki. *Diagnosis and Fault-Tolerant Control.* Springer, 2 edition, 2006.

U. Brehme, U. Stollberg, R. Holz, and T. Schleusener. Alt pedometer-new sensor-aided measurement system for improvement in oestrus detection. *Computers and Electronics in Agriculture*, 62(1):73–80, 2008. ISSN 01681699.

C. G. Cassandras and S. Lafortune. *Introduction to Discrete Event Systems.* Springer, 2 edition, 2008.

W. J. Eradus and M. B. Jansen. Animal identification and monitoring. *Computers and Electronics in Agriculture*, 24(1/2):91–98, 1999.

W. J. Eradus, H. Scholten, and A. J. Udink-ten Cate. Oestrus detection in dairy cattle using a fuzzy inference system. *Control applications and ergonomics in agriculture CAEA ' 98: A Proceedings volume from the IFAC Workshop, Athens, Greece, 14 17 June 1998*, 1999.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Automation of oestrus detection in dairy cows: a review. *Livestock Production Science*, 75(3):219–232, 2002.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Oestrus detection in dairy cows based on serial measurements using univariate and multivariate analysis. *Archiv fur Tierzucht*, 46(2):127–142, 2003.

R. I. Jónsson, T. Björgvinsson, M. Blanke, N. K. Poulsen, S. Højsgaard, and L. Munksgaard. Oestrus detection in dairy cows using likelihood ratio tests. In *Proceedings of the 17th World Congress, The International Federation of Automatic Control, Seoul, Korea, July 6-11, 2008*, 2008.

K. Maatje, M. d. Mol, R., and W. Rossing. Cow status monitoring (health and oestrus) using detection sensors. *Computers and Electronics in Agriculture*, 16(3):245–254, 1997.

M. d. Mol, R. and E. Woldt, W. Application of fuzzy logic in automated cow status monitoring. *Journal of Dairy Science*, 84(2):400–410, 2001.

M. d. Mol, R., H. Kroeze, G., M. F. H. Achten, J., K. Maatje, and W. Rossing. Results of a multivariate approach to automated oestrus and mastitis detection. *Livestock Production Science*, 48(3):219–227, 1997.

M. d. Mol, R., A. Keen, H. Kroeze, G., and M. F. H. Achten, J. Description of a detection model for oestrus and diseases in dairy cattle based on time series analysis combined with a kalman filter. *Computers and Electronics in Agriculture*, 22(2/3):171–185, 1999.

L. Nebel, R., G. Dransfield, M., M. Jobst, S., and H. Bame, J. Automated electronic systems for the detection of oestrus and timing of ai in cattle. *Animal Reproduction Science*, 60/61:713–723, 2000.

Paper D

Oestrus Detection in Dairy Cows from Activity and Lying Data using on-line Individual Models[1]

Jónsson, R., Blanke M., Poulsen N. K., Caponetti, F. and Højsgaard, S.

Abstract

Automated monitoring and detection of oestrus in dairy cows is attractive for reasons of economy in dairy farming. While high performance detection has been shown possible using high-priced progesterone measurements, detection results were less reliable when only low-cost sensor data were available. Aiming at improving detection scheme reliability with the use of low-cost sensor data, this study combines information from step count and leg tilt sensors. Introducing a lying balance for the individual animal, a novel change detection scheme is derived from observed distributions of the step count data and the lying balance. Detection and hypothesis testing are based on generalised likelihood ratio optimisation combined with time-wise joint probability windowing based on the duration of oestrus and oestrus intervals. It is shown to be essential that cow-specific parameters and test statistics are derived on-line from data to cope with behaviours of individuals. Performance is validated on 18 sequences

of data where definite proof of prior oestrus was available in form of subsequent pregnancy. These data were extracted from data sequences from 44 dairy cows over an 8 months period. The results show sensitivity 88.9% and error rate 5.9.%, which is very satisfactory when only cheap sensor data are used.

Keywords: statistical change detection, lying balance, dairy cows

D.1 Introduction

Assessment and classification of oestrus in dairy cows is a field in constant development. The motivation is to timely detect animals in need of attention from the farm personnel to obtain artificial insemination. Fast and accurate detection of oestrus is essential from an economical point of view, for reproduction and for maintaining milk production.

The period from parturition until first oestrus is varying between types of cattle and between parturition. According to Crowe [2008] dairy cows generally ovulate the first post-partum dominant follicle after approximately 15 days provided that the dairy cows are sufficiently nourished. The first post-partum ovulation is usually not associated with the expression of oestrus and is followed by a short 9-11 days cycle where the dairy cows most often begin to show signs of oestrus, Crowe [2008], and subsequently goes into oestrus with a certain cycle until pregnancy occurs. Holstein post-partum dairy cows have a 18-23 days cycle. Correct identification of the oestrus is of a paramount importance for the farmer as successful insemination is possible only within a short time-window after the oestrus.

Automatic detection of oestrus in dairy cows using measurements of activity and other traits has been the subject of several studies. Moore and Spahr [1991], Liu and Spahr [1993] and Roelofs et al. [2005], used statistical tests where a mean of recent activity was compared to hindcast mean values. Analyses of time series, where parameters were estimated by linear Kalman filters, were presented in Maatje et al. [1997], de Mol et al. [1997] and de Mol et al. [1999]. Further, Eradus et al. [1999], de Mol and Woldt [2001], Firk et al. [2003b] and Liberati and Zappavigna [2009] detected oestrus by Fuzzy logic methods. A generalised likelihood ratio (GLR) test was adopted to observed distributions of activity data by Jónsson et al. [2008] and further improved in Zarchi et al. [2009] by fuzzy logic classification of the alerts utilising the period between oestruses. Measurements of milk progesterone were used by Friggens et al. [2008] and O'Connell et al. [2011] combined measurements of milk progesterone level and activity, both with satisfactory results, but at a penalty in expense of measurements. Methods of automated oestrus detection were reviewed by Eradus and Jansen [1999] and Firk et al. [2002]. Conditions for identification of oestrus and successful artificial insemination have become more difficult in recent years due to reduced expression and decreased duration of oestrus Dobson et al. [2008].

The quality of results, viewed as detection probability versus number of false alerts, has thus far been satisfactory only with use of expensive hormone monitoring. Technological developments in instrumentation have taken place and

Rorie et al. [2002] compared electronic technologies aimed at oestrus detection. New devices that combine sensing of activity with lying/standing measurements have also been introduced, see Brehme et al. [2008].

This paper introduces a *lying balance* to estimate dairy cows' motivation to lie down. A new approach is suggested where statistical change detection is employed on the combination of the lying balance and step count measurements. Adaptation of the statistical change detector is investigated under normal and oestrus behaviours for individual dairy cows. Estimating parameters on-line makes it possible to adapt to individual behaviours of animals. Utilising also the expected duration of oestrus, and the length of the oestrus cycle in the detector design are shown to have clear advantages in terms of favourable false alert and correct detection probabilities. Ground truth for oestrus is taken to be subsequent pregnancy.

D.2 Materials and methods

Data were recorded at the research facility at the Danish Cattle Research Centre in Foulum, Denmark, which is a loose housing system with cubicles and milking robots.

D.2.1 Data

The dataset consists of measurements of steps and lying/standing behaviour recorded by the commercially available activity sensor IceTag3D®.[1] The use of IceTag3D® for monitoring was addressed by Trénel et al. [2009] and Munksgaard et al. [2006]. The sensor is attached to the dairy cows leg and assess the dairy cows activity in terms of the variables *lying*, *standing*, *motion index* and *step count* using 3d-accelerometer technology. The sample period of the IceTag3D® is configurable and is chosen as 1 minute, which is also the time-resolution used throughout this study.

The first three variables available from the IceTag3D® are the percentage of the sample period spent in each of the three states. The fourth variable, the *step count*, is the number of steps in each sample period.

The variables *lying* and *standing* gives the percentage of the sampling period spent in each of the two states; the *motion index* is a measure of how much the

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[1]IceTag3D® is a trademark of IceRobotics Ltd, Edinburgh, Scotland UK

cow has moved in the sampling period and *step count* is the number of steps in each sampling period. The variables *lying* and *step count* are used for assessing lying behaviour and activity in this paper. The variable *lying* is, in accordance with Munksgaard et al. [2006], discretised into a binary variable y_m as follows: y_m is 1 if less than 50% of the mth minute is spent lying and and 0 otherwise.

Decisions about insemination were made by the staff at the Danish Cattle Research Centre, according to methods described in Løvendahl and Chagunda [2010]. Not all inseminations are associated with real oestruses as insemination might be performed on the basis of false alert or erroneous interpretation of a cow's behaviour. Therefore, to ensure that the data-set was based on true cases of oestrus, only data from periods around inseminations that led to confirmed pregnancy were used to extract the data used in this study. No IceTag3D® measurements were available to the staff.

IceTag3D® recordings, that were observed from Sept-2008 to Apr-2009, were available for a total of 88 cows over periods of varying time length and with a varying number of *measuring sequences*. A measuring sequence is the time period in which an IceTag3D® has been continuously attached to a cow's leg. Wireless transfer of data from the IceTag3D® to a computer was done by manually holding a data reader close to the IceTag3D®. This was required with 60 days intervals due to device storage limits.

Data sequences used for assessing the performance of the oestrus detection algorithm were selected in a time window around a successful insemination. As there are typically between 18 and 23 days between two oestruses (Chaudhari and Sabo [2006] and Crowe [2008]), 2 weeks of data before and after each successful insemination were selected. This ensured each data sequence comprised only one oestrus case. This approach is identical to that of Løvendahl and Chagunda [2010] and similar to experiment techniques by Firk et al. [2003a] and Firk et al. [2003b]. Therefore, for each dairy cow, a data sequence was identified by investigating if the cow was inseminated during the time span from 2 weeks after the beginning until 2 weeks before the end of the available data and simultaneously that the cow became pregnant. Out of the dairy cows studied, 26 became pregnant but, 8 had no data during the day of insemination. Therefore, only 18 dairy cows hence remained in the study data-set. These are subsequently referred to as the *study cows*. Of the 62 cows that did not get pregnant, 18 cows were inseminated while wearing an IceTag3D® without becoming pregnant and 44 were not inseminated while wearing an IceTag3D®.

Table D.1 shows the grouping of dairy cows that formed the basis for the selection of the *study cows*. The group of *study cows* is a union of the groups, *approx. 4 weeks of consecutive data*, *data logging issues outside oestrus* and *artifacts in data outside oestrus*.

Table D.1: Dataset overview

Description	Number
Dairy cows with an IceTag® device	88
No insemination while wearing IceTag	44
Cows without successful insemination	18
Cows with successful insemination *(below):*	
Approx. four weeks of consecutive data	8
Data logging issues outside oestrus	5
Artifacts in data outside oestrus	5
No data during oestrus	8

Periods with missing or unreliable data in the study data-set necessary occur when transferring sensor data so data-processing had to deal with these and other artifacts.

D.2.2   Statistical change detection

To set the concepts and notation, a brief summary of statistical change detection is given below. Consider the idealised situation where the task is to identify in which of two states (normal or oestrus) a cow is in based on data in a time window $[j, m]$ containing $N_m(j) = m - j + 1$ observations. If the observed data of all *study cows* belong to distributions with known parameters during normal and oestrus behaviour, an optimal detector can be constructed based on the Neyman–Pearson theorem (Neyman and Pearson [1933], see also Basseville and Nikiforov [1993], pp. 112).

If the difference in behaviours emerge as a change in mean value, hypotheses become

$$\mathcal{H}_0 : \mu_{m'} = \mu_0 \ \text{ versus } \ \mathcal{H}_1 : \mu_{m'} = \mu_1 \ \text{ for } j \leq m' \leq m \tag{1}$$

where m' is the time and μ_0 and μ_1 are the mean values of normal and oestrus behaviours, respectively.

In practice, when dealing with observations of animal behaviour, the distributions are not known and the observations are not independent. First of all, the means μ_1 and μ_0 are unknown. Secondly, μ_1 and μ_0 can not be assumed to be the same for all dairy cows as the dairy cows are individuals that behave differently. The detection can then be based on the generalised likelihood ratio (hereafter abbreviated GLR) test (see e.g. Gustafsson [2000], pp. 350 or Blanke et al. [2006], pp. 252 for an implementation). The GLR for an unknown change

in mean value of the observation x_m is defined as

$$S_m(\mu_1, j) = \sum_{m'=j}^{m} \ln\left(\frac{p_{\mu_1}(x_{m'})}{p_{\mu_0}(x_{m'})}\right),$$ (2)

where m is the current time and j (where $j \le m$) is the time for the onset of the change. The GLR is therefore the sum of log-likelihood ratios over the window $[j, m]$ containing $N_m(j)$ observations. Notice that S_m in (2) also depends on μ_0. Estimation of μ_0 will be discussed below; for now it is assumed that μ_0 is known.

As neither the time j for the onset of the change nor the mean value μ_1 are known, these quantities need to be estimated. This can be done by a maximum likelihood estimate of both values. For a fixed window $[j, m]$, maximise $S_m(\mu_1, j)$ with respect to μ_1. This gives $\hat{\mu}_{1m}(j)$. Subsequently $S_m(\hat{\mu}_{1m}(j), j)$ is maximised with respect to the time j of the onset of change. That is,

$$\hat{S}_m = \max_{j=1,\ldots,m} \max_{\mu_1} S_m(\hat{\mu}_{1m}(j), j).$$ (3)

The double maximisation in (3) can be made for example if the probability density functions belong to the *exponential family* of distributions (Basseville and Nikiforov [1993], pp. 52). For a given window $[j, m]$ of size $N_m(j)$ the estimate for μ_1 is

$$\hat{\mu}_{1_m}(j) = \sum_{m'=j}^{m} x_{m'}/N_m(j).$$ (4)

This value is inserted into (2).

In the following, $\hat{S}_m$ is referred to as the decision function. If $\hat{S}_m$ exceeds a pre-defined threshold, a change is declared.

The parameter μ_0 is unknown and has to be estimated on-line. This is done using an exponentially weighted moving average (EWMA) (Hunter [1986]) which is defined as

$$\hat{\mu}_{0_m} = (1 - \lambda_\mu)\hat{\mu}_{0_{m-1}} + \lambda_\mu x_m,$$ (5)

where $\lambda_\mu \in [0, 1]$ is a memory factor that controls the weighting between the influence of the new observation x_m and earlier values of the estimated mean $\hat{\mu}_{0_{m-1}}$. A high (low) value for λ_μ will make $\hat{\mu}_{0_m}$ adapt rapidly (slowly) to any change in the mean value.

When tuning the λ_μ in the GLR detector the expected length of the oestrus cycle is taken into account such that the mean estimate converges towards the mean of the normal behaviour between consecutive oestruses.

D.2.3 Adapting the GLR

The GLR algorithm was further adapted to the application of detecting oestrus by including restrictions on the direction and the duration of the change to be detected. The GLR is a two sided test but for the detection of oestrus the direction is known. Therefore, the decision function is set to zero whenever $\hat{\mu}_{1_m}(j)$ is not on the same side of $\hat{\mu}_{0_m}$ as the change that is supposed to be detected. This is shown in (9) and (17). Regarding the duration of change, the attention is restricted to a change that started for at least L and at the most U minutes ago and the decision function in (3) changes to

$$\hat{S}_m = \max_{j=m-U,\ldots,m-L} S_m(j). \tag{6}$$

where $U < m$ and $L < U$. Introducing these restrictions on change occurred serves two purposes. The first is to limit the number of calculations because maximisation is over $j = m - U, \ldots, m - L$, rather than over $j = 1, \ldots, m$ as in (3); the calculation is done only over $U - L + 1$ instead over m minutes. The second is to improve the detection performance utilising the expected 18 hours duration of oestrus. Setting the lower limit L equal to 12 hours reduces the probability of getting a false alert due to a change in the behaviour lasting say for example 2 hours. Although the limit is set to 12 hours the algorithm could be able to detect an oestrus lasting for less than 12 hours. The upper limit U is set to 24 hours and has the main purpose of reducing the computational load.

A summary of the change detection procedure is presented in D.I.

D.2.4 Detection using step count

The step counts were investigated by viewing the pooled step count observations of the *study cows* under normal conditions and under oestrus. Observations belonging to the oestruses were defined as the 18 hour window containing the largest number of steps in a sliding window moved from 36 hours before midnight before the day of insemination to 36 hours after midnight before the day of insemination. Thus 90 hours of observations are included in the search for the oestrus data. In other words denoting m_o as the midpoint of the 18 hour window

with the largest number of steps and m_r as the minute of insemination reference at midnight before the day of the successful insemination the midpoint of the window is found as

$$m_o = \operatorname*{argmax}_{m=m_r-24\times 60,\ldots,m_r+24\times 60} \sum_{m'=m-9\times 60}^{m+9\times 60} z_{m'} \tag{7}$$

where $z_{m'}$ is the step count at minute m' (argmax returns the minute m that maximises the expression). Data from this window are in the following considered to belong to the oestrus. A histogram of the pooled step count data from the *study cows* set is shown in Figure D.1 for normal behaviour and oestrus.

The figure shows that observations of normal and oestrus behaviours differ both with respect to mean values and variance. The number of steps per minute is approximated by an exponential distribution $p_\mu(z_m) = 1/\mu \times \exp(-z_m/\mu)$ which is parameterised by only one parameter, μ. Even though this approximation is rather crude, as seen in in Figure D.1, it is useful for the purpose of diagnosis since a change in the parameter μ affects both mean and variance.

For detecting a change in the step count based on the hypotheses in (1) and described by exponential probability density functions, the GLR in (2) is

$$\begin{aligned} S_m(\mu_1^z, j) &= \sum_{m'=j}^{m} \left(\log\left(\frac{\mu_0^z}{\mu_1^z}\right) + \left(\frac{1}{\mu_0^z} - \frac{1}{\mu_1^z}\right) z_{m'} \right), \\ &= N_m(j)\log\left(\frac{\mu_0^z}{\mu_1^z}\right) + \left(\frac{1}{\mu_0^z} - \frac{1}{\mu_1^z}\right) \sum_{m'=j}^{m} z_{m'}, \end{aligned} \tag{8}$$

where μ_0^z and μ_1^z are the mean values of the step count during normal and oestrus behaviours, respectively. In practice μ_1^z is replaced with its MLE (4) and μ_0^z is replaced by $\hat{\mu}_{0_m}^z$ from (5). The λ_μ in (5) is selected as $\lambda_\mu = 0.0001$.

Including the classification for the correct direction of change and the restrictions on the duration of the change described in Section D.2.2 the cumulative sum of log-likelihoods is

$$\begin{aligned} S_m(j) = \quad & N_m(j)\log\left(N_m(j)\frac{\hat{\mu}_{0_m}^z}{\displaystyle\sum_{m''=j}^{m} z_{m''}} \right) \\ &+ \frac{1}{\hat{\mu}_{0_m}^z} \sum_{m'=j}^{m} z_{m'} - N_m(j), \end{aligned} \tag{9}$$

if $\hat{\mu}_{1_m}^z(j) \geq \hat{\mu}_{0_m}^z$ and 0 otherwise.

Thus, whenever $\hat{\mu}^z_{0_m} > \hat{\mu}^z_{1_m}(j)$ the cumulative sum of log-likelihoods for j is set to zero. Thereby the algorithm avoids being triggered by detecting a negative change in mean. With the slowly changing $\hat{\mu}^z_{0_m}$ the mean can be assumed to be constant within the time window of the GLR, the maximum size of which is $U - L + 1$.

D.2.5 Detection using lying behaviour

Decreased lying time is an expected change in behaviour during oestrus (Livshin et al. [2005]). Therefore a change in lying time is used as an indicator for oestrus. The lying time is modelled by a lying-balance, which is described in the following.

D.2.5.1 Lying-balance

The lying-balance is a quantity which indicates the internal motivational state of the cow. The lying-balance is increasing when the cow is lying and decreasing when the cow is standing or walking. Hence a low lying-balance is a sign of a high motivation to lie down.

The lying-balance at minute m is modelled as exponential functions

$$
\begin{aligned}
\gamma_m &= \exp\left(-\kappa - (m - m_c)/\mu^s_{m_c}\right) && \text{if } y_m = 1 \\
\gamma_m &= 1 - \exp\left(-\kappa - (m - m_c)/\mu^l_{m_c}\right) && \text{if } y_m = 0
\end{aligned}
\tag{10}
$$

where m_c is the time for the most recent change of state and y_m is the currently observed status, $y_m = 1$ for lying and $y_m = 0$ for standing.

The parameter κ serves the purpose of setting the correct start value for γ_m after each change between the two states lying and standing. Hence informing the value of the lying-balance that was at m_c, thus making the model continuous. The parameter μ^s controls how fast the model decays from 1 to 0 and correspondingly μ^l controls how fast the model grows from 0 to 1.

Modelling the lying behaviour as exponential functions is supported by the histograms of the pooled observations of the duration of each standing (lying) period. From Figure D.2 it appears that the duration of the lying and standing periods are approximately exponentially distributed.

For determining μ^s and μ^l the assumption was made that the time that the cow spends standing during one day would let the lying-balance decay from 1 to 0, if

standing continuously. For this assumption the approximation is done that the standing periods of the day have the same effect as one standing period which duration is equal to the sum of standing periods that day. Thereby denoting D^s as the number of minutes standing each day and assuming that the lying-balance decays from one to a value close to zero ($\gamma_m = 0.005$) if standing continuously for D^s minutes, μ^s can be found by solving (10) with respect to μ^s when $y_{m\ldots m_c} = 1$ which gives

$$\mu^s = \frac{D^s}{-\ln(0.005)} \approx \frac{D^s}{5}. \tag{11}$$

Similarly assuming that the lying-balance should be able to grow from zero to close to one ($\gamma_m = 0.995$) during the time spent lying each day $\mu^l = D^l/5$.

The balances should adapt locally because if a dairy cows standing time was recently increased then μ^s should also increase and μ^l should decrease. This is achieved by updating these two parameters as

$$
\begin{aligned}
\mu_m^s &= \mu_{m-1}^s + \frac{1}{T_m}\left(\frac{D_m^s}{5} - \mu_{m-1}^s\right) \\
\mu_m^l &= \mu_{m-1}^l + \frac{1}{T_m}\left(\frac{D_m^l}{5} - \mu_{m-1}^l\right) \\
T_m &= \lambda T_{m-1} + 1 \quad T_0 = 0
\end{aligned}
\tag{12}
$$

where λ is the forgetting factor, which in this study is chosen as $\lambda = 0.99$. The parameter D^s is the number of minutes where a cow is standing in the window $[m - 24 \times 60, m]$ and correspondingly D^l is the number of minutes lying.

Notice, for small values of T_m the estimator in (12) is close to an ordinary least squares estimate of the mean of $D_m^s/5$ and $D_m^l/5$. For larger values of T_m it coincides with an exponentially weighted moving average.

Finally, κ is found at every change between the states lying and standing by solving (10) with respect to κ

$$
\begin{aligned}
\kappa &= -\log \gamma_{m_c} & \text{if } y_{m_c} = 0, \\
\kappa &= -\log(1 - \gamma_{m_c}) & \text{if } y_{m_c} = 1.
\end{aligned}
\tag{13}
$$

The procedure for calculating the lying-balance is described in D.II. An example of the lying-balance is given in Figure D.3.

D.2.5.2 Detection of change in lying-balance

The properties of the lying-balance during normal and oestrus behaviour respectively were investigated by viewing of the pooled data of the calculated lying-balance for the *study cows*. A histogram of the pooled behaviour is shown in Figure D.4. The normal behaviour is assumed to belong to be normal distributed although the histogram seems a bit right skewed. The oestrus behaviour is assumed to belong to an exponential distribution. Using a GLR test, this distribution leads to the decision function

$$
\hat{Q}_m = \max_{j=1,\ldots,m} \max_{\mu_1^\gamma}
$$
$$
\left(N_m(j) \log\left(\frac{\sqrt{2\pi V_0^\gamma}}{\mu_1^\gamma} \right) + \sum_{m'=j}^{m} \left(\frac{(\gamma_{m'} - \mu_0^\gamma)^2}{2V_0^\gamma} - \frac{\gamma_{m'}}{\mu_1^\gamma} \right) \right) \tag{14}
$$

where μ_0^γ and V_0^γ are the mean value and variance of the lying-balance during normal behaviour and μ_1^γ is the mean value of the lying-balance during oestrus behaviour. In the same way as in Section D.2.4, μ_1^γ in (14) is replaced with its estimate (4) and μ_0^γ with $\hat{\mu}_{0_m}^\gamma$ (5), where $\lambda_\mu = 0.0001$.

The variance of the normal behaviour is estimated on-line using an exponentially weighted moving variance (EWMV) estimation (MacGregor [1993])

$$
\hat{V}_{0_m}^\gamma = (1 - \lambda_v)\hat{V}_{0_{m-1}}^\gamma + \lambda_v(\gamma_m - \mu_0^\gamma)^2 \tag{15}
$$

where λ_v is a memory factor for the variance estimation, which is selected as $\lambda_v = 0.0001$. The parameter V^γ in (14) is replaced by $\hat{V}_{0_m}^\gamma$.

Similar to the step count case the GLR for the lying-balance is also done one-sided. As the value of the lying-balance is expected to decrease during oestrus the GLR is set to zero when the MLE estimate of the mean value of the change is higher than the mean value of the normal behaviour. The decision function therefore becomes

$$
\hat{Q}_m = \max_{m-U \leq j \leq m-L} Q_m(j) \tag{16}
$$

where the cumulative sum of log-likelihoods becomes

$$
Q_m(j) = N_m(j) \log \left(N_m(j) \frac{\sqrt{2\pi \hat{V}_{0_m}^\gamma}}{\sum\limits_{l=j}^{m} \gamma_l} \right)
$$
$$
+ \frac{1}{2\hat{V}_{0_m}^\gamma} \sum_{m'=j}^{m} (\gamma_{m'} - \hat{\mu}_{0_m}^\gamma)^2 - N_m(j) \tag{17}
$$

if $\hat{\mu}_{1_m}^\gamma(j) \leq \hat{\mu}_{0_m}^\gamma$ and 0 otherwise.

D.2.6 Combined detection using step count and lying behaviour

The two decision functions established in (6) and (16) can be combined to achieve enhanced detection results.

Figure D.5 shows a scatter-plot of the two decision functions and shows how these are correlated during oestrus. The combination of the decision functions based on step count and lying behaviour (calculated using (6) and (16)) is done using an exponentially weighted moving covariance. The calculation is based on methods for estimation of variance and covariance matrices described in MacGregor [1993] and Hawkins and Maboudou-Tchao [2008]. Denoting the exponentially weighted moving covariance by $\hat{R}_m$ gives

$$
\hat{R}_m = (1 - \lambda_r)\hat{R}_{m-1} + \lambda_r \hat{S}_m \hat{Q}_m \tag{18}
$$

where λ_r is the memory factor, which is set as $\lambda_r = 0.995$.

D.2.6.1 Adaptive detection threshold

According to the Neyman-Pearson theorem, a threshold can be found that gives a certain probability of detection and a certain probability of false detection for a decision function if its distribution is known. Deciding a distribution for the combined decision function $\hat{R}_m$, in (18), is quite difficult, however. This decision function is a combination of (1) a GLR test for two exponential distributions and (2) a GLR for normal behaviour described by a normal distribution and oestrus behaviour described by an exponential distribution. Additionally, determining a distribution for each of the GLRs in (6) and (16) is not straightforward either

since the tests have the maximisation with respect to the onset of change and the algorithms are furthermore one-sided.

The combined decision function in (18) is generally close to zero with few extreme values. As the distribution is not known, an adaptive detection threshold can be based on the historical maximum values of the decision function. The decision function can be zero or close to zero for relatively long periods. Therefore it is necessary to set a lower limit (h_{min}) on the adaptive threshold as it otherwise would become too sensitive. Some dairy cows occasionally seem to display behaviour similar to oestrus behaviour although not in oestrus. In this case the decision function would increase (and perhaps issue a false alert). In order not to let this increase in the decision function raise the threshold to an unreasonably high level a maximum limit (h_{max}) is set for the adaptive threshold.

Denoting the detection threshold by h and the minimum and maximum thresholds as h_{min} and h_{max}, respectively, the detection threshold is found as

$$h = \max_{j=m-H-\upsilon,\ldots,m-\upsilon} \hat{R}_j \times c$$

$$h_m = \max(h_{min}, \min(h_{max}, h)) \qquad (19)$$

where H is the historical time horizon, υ is a delay and c is a scaling factor. The parameter υ ensures that the threshold does not grow with a growing decision function due to the present oestrus and is selected as $\upsilon = 18 \times 60$. The historical horizon is selected as large as possible without including an earlier oestrus. The sum of H and υ should therefore be less than what corresponds to the expected 18 days minimum oestrus cycle Crowe [2008]. This leads to $H = 16 \times 24 \times 60$. The scaling factor is introduced to allow the decision function to deviate above the maximum values within the historical horizon. This factor should be large enough to prevent false alerts without preventing an oestrus alert from being issued in connection with a real oestrus. The multiplication factor is chosen as $c = 3$ and the minimum and maximum values are chosen as $h_{min} = 9 \times 10^4$ and $h_{max} = 8 \times 10^5$.

The detection algorithm will issue an oestrus alert whenever $\hat{R}_m \geq h_m$ and reset the alert again when $\hat{R}_m < h_m \times 0.01$.

Parameters for adaptive thresholds were also chosen for the single trait detectors in (6) and (16). This was done to be able to compare the combined detection in (18) with the results of the single trait detectors. For the step count detection the multiplication factor was again chosen as $c = 3$ and the minimum and maximum values as $h_{min} = 300$ and $h_{max} = 700$. For the lying-balance detection the parameters were selected as $c = 2$, $h_{min} = 1100$ and $h_{max} = 1500$.

D.3 Results

This section describes the inspection of data properties including selection of probability distributions as well as the performance test of the detection algorithm. Firstly the data are investigated and then the detection algorithm is tested on the behaviour observations of step activity and the lying-balance of the lying behaviour.

D.3.1 Selection of distributions

A part of the detector design includes the selection of which type of distribution the statistical change detector should be based on. Distributions for the detection algorithms were selected on the basis of histograms the pooled observations during normal and oestrus. Considerations for the step count data and the lying-balance respectively are treated below.

D.3.1.1 Distribution for describing the step count observations

Figure D.1 shows histogram of the number of steps per minute for the normal and oestrus behaviour and plots of probability density functions of exponential distributions fitted to the data.

The distributions applied for describing the normal and oestrus behaviour in the GLR were exponential. As mentioned in Section D.2.4 the mean and standard deviation of the exponential distribution are the same. The MLE estimates of mean value and standard deviation for the observations of the normal behaviour plotted in Figure D.1.(a) were found as $\hat{\mu}_0^z = 1.1$ and $\hat{\sigma}_0^z = 2.5$. Those of the oestrus behaviour in Figure D.1.(b) were found as $\hat{\mu}_1^z = 4.0$ and $\hat{\sigma}_1^z = 5.5$. The MLE estimates for the mean and standard deviations are not the same but the exponential distributions were nevertheless selected for the GLR for mathematical convenience. The implementation is relatively simple and the fact that both mean value and standard deviation change during oestrus support the selection of the one parameter distribution for the GLR.

It has been found that square root transformed step count data fits better to the exponential distribution than step count data itself. The approach using the square root transformed step count data in constructing the decision functions was also tested. This lead to slightly poorer detection results. We suspect that this reduced performance is due to that the square root transformation reduces

(a) Non-oestrus (normal) behaviour   (b) Oestrus behaviour
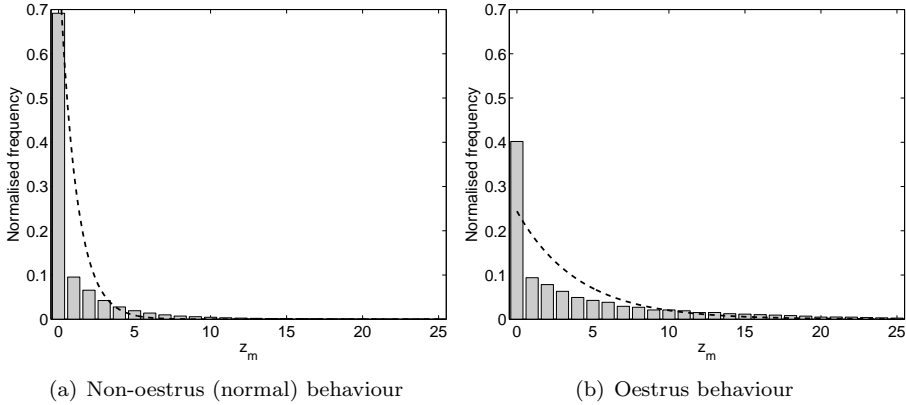
Figure D.1: Histograms of number of steps per minute for the *study cows* under normal and oestrus behaviours respectively. Probability distribution functions of fitted exponential distributions are plotted with dashed lines.

the difference in the distributions between the normal and the oestrus cases.

D.3.1.2   Lying/standing data

Figure D.2 shows histograms of the pooled sojourn time spent in the states lying and standing for the *study cows*. The figure also shows probability density functions fitted to the data.

It appears from Figure D.2 that the exponential distribution gives a decent fit of the data. The MLE estimates of the mean value and standard deviation of the sojourn lying durations are $\mu^l = 64.2$ and $\sigma^l = 47.9$. Those of the standing durations are $\mu^s = 66.3$ and $\sigma^s = 68.3$.

An example of the lying-balance is given in Figure D.3 which shows the calculated lying-balance for one cow during 2 days of normal behaviour and 2 days where oestrus occurs.

Figure D.3 shows how the lying-balance decreases during oestrus. The histograms of the normal and oestrus behaviour are shown in Figure D.4. The figure also shows probability density functions of a normal distribution fitted to the normal data and an exponential distribution fitted to the oestrus data.

(a) Lying   (b) Standing
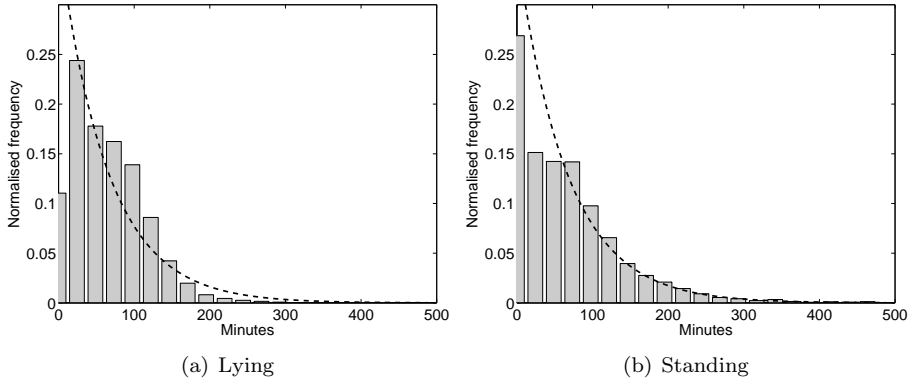
Figure D.2: Histograms of pooled sojourn time in the states lying and standing for the *study cows*. Probability distribution functions of fitted exponential distributions are plotted with dashed lines.

In accordance with Figure D.4 the distributions for the lying-balance during normal and oestrus behaviour in the GLR were approximated by exponential and normal probability density functions, respectively. The MLE estimates of mean value and standard deviation of the normal behaviour in Figure D.4.(a) were determined to be $\hat{\mu}_0^\gamma = 0.50$ and $\hat{\sigma}_0^\gamma = 0.18$. For the oestrus behaviour in Figure D.4.(b), the mean value and standard deviation were $\hat{\mu}_1^\gamma = 0.29$ and $\hat{\sigma}_1^\gamma = 0.21$.

D.3.2   Combination of decision functions

As mentioned in Section D.2.6 the combined detection signal is implemented as an exponentially weighted moving covariance of the two decision functions in (6) and (16). The correlation between the two decision functions is shown in Figure D.5, a scatter plot of the step count decision function versus that of the lying-balance. The Figure also shows the minimum and maximum thresholds, h_{min} and h_{max}.

Figure D.5 shows that the two decision functions are correlated during oestrus. The figure therefore supports the selection of the combination method in Eq. (18).

<div align="center">(a) Non-oestrus   (b) Oestrus</div>
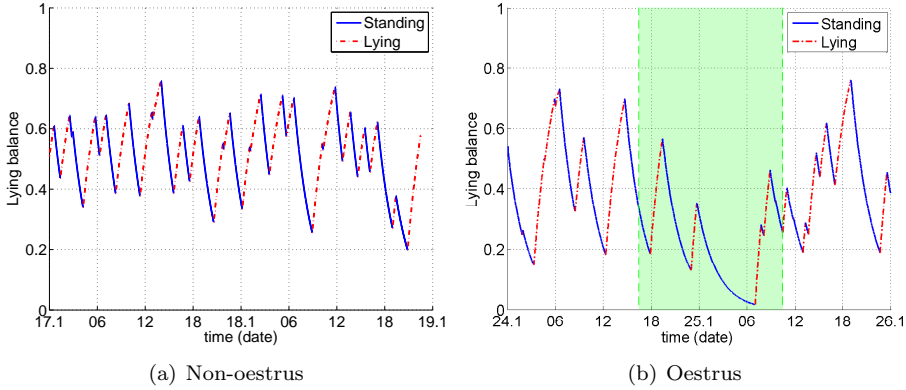
Figure D.3: An example of the lying-balance. The shaded area shows the 18 hour period where the largest sum of step activity around insemination was observed (see (7) in Section D.2.4)

D.3.3   Detection results

The performance of the detection algorithm was assessed by applying the algorithms described in Sections D.2.4-D.2.6 to the observations described in Section D.2.1. The detection results are presented as *sensitivity* (sens), *specificity* (spec) and *error ratio* (erat)

$$
sens = \frac{tp}{tp + fn}
$$
$$
spec = \frac{tn}{tn + fp} \tag{20}
$$
$$
erat = \frac{\widehat{fp}}{tp + \widehat{fp}}
$$

where tp, fp, fn, tn and $\widehat{fp}$ are defined as follows.

Let an *oestrus window* be defined as the time interval 36 hours before to 12 hours after 6 am of the day of insemination that led to pregnancy. A detections is considered to be true positive (tp) if the detection event lies within the oestrus window. If outside this window, the event is considered a false positive (fp). If no detection event falls within an oestrus window, this counts for one false negative (fn). A day with no detection event, where the day is outside the oestrus windows, is counted as a true negative (tn).

Therefore, the measure of sensitivity is a ratio between quantities which are

(a) Non-oestrus   (b) Oestrus
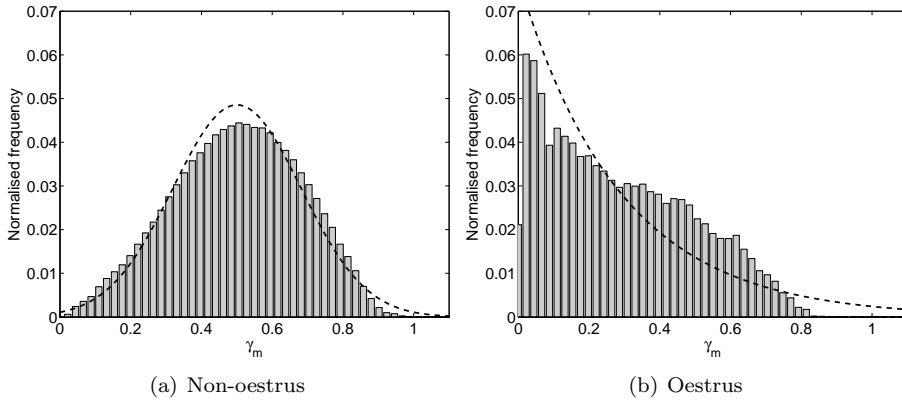
Figure D.4: Histograms of lying-balance for the *study cows* under normal behaviour and oestrus behaviour respectively. Probability distribution functions of a normal distribution fitted to the normal data and an exponential distribution fitted to the oestrus data are plotted with dashed lines.

inside the 48 hour oestrus window. The specificity is the quotient of quantities defined within a 24 hour observation period. Defining $\widehat{fp}$ as a detection taking place outside the oestrus window, but referring to 48 hour intervals, the error ratio is calculated between events that relate to 48 hour windows.

The detection results are listed in Table D.2.

The results listed in Table D.2 show that the combined detection gives improved results compared with the results of the single trait detectors on the activity and the lying-balance.

The detection results for individual dairy cows with respect to the oestrus reference and the period of valid detection are plotted in Figure D.6.

In Figure D.6 it is shown how the detection events for cows no. 7 and 17 are classified as true although initiated before the oestrus window. In the case of cow no. 7 there are two detections associated with the oestrus. The first detection is initiated 6 hours before the oestrus window and was reset inside the window. The second detection is initiated and reset inside the oestrus window. It is also seen in Figure D.7 (a) how both detections are initiated on account of the same increase in the activity signal. Both detections are therefore classified as one tp. In the case of cow no 17 there is a detection that was triggered 7 hours before the oestrus window and was reset 13 hours inside the window. This detection
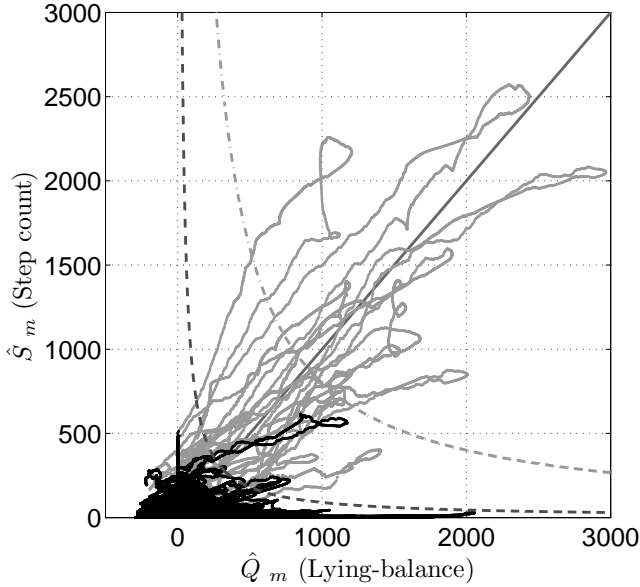
Figure D.5: Scatter plot of the decision functions of (6) and (16). The values during oestrus are shown in gray dots and during periods of normal behaviour in black dots. The thresholds h_{min} and h_{max} are shown as dashed and dash-dotted lines.

is associated with oestrus and is therefore classified as tp.

A detection example is shown in Figure D.7.

D.4   Discussion

Measurements from IceTag3D® that measure both activity and lying behaviour were used to investigate whether combined measurements of activity and lying behaviour could improve reliability of the oestrus detection. The results showed that combined step count and lying balance detector significantly reduces the probability of false alerts (error ratio) with respect to using either activity or lying behaviour as the sole measurement. A further scrutiny of missed detections was conducted and reasons for missed detections on dairy cows 1 and 11 were found. The maximum likelihood estimates of mean value and standard deviation for the observations of the normal behaviour were $\hat{\mu}_0^z = 0.9$ and $\hat{\sigma}_0^z = 2.2$. Those of the oestrus behaviour were $\hat{\mu}_1^z = 1.6$ and $\hat{\sigma}_1^z = 2.8$. Comparing these results

Table D.2: Summary of detection results of each method for 18 dairy cows given as true positive (tp), true negative (tn), false positive (fp) and false negative (fn), sensitivity (sens), specificity (spec) and error ratio (erat)

	Step count	Lying balance	Combined
tp	16	9	16
tn	483	484	485
fp	3	2	1
$\hat{f}p$	3	2	1
fn	2	9	2
$sens$	88.9%	50.0%	88.9%
$spec$	99.4%	99.6%	99.8%
$erat$	15.8%	18.2%	5.9%

with those of the pooled data for all the 18 *study cows* the difference in the estimated values is much smaller for these dairy cows than for the whole group. With hardly any difference between the measured behaviours of these two cows in normal and in oestrus, detection would be very difficult with any method.

Previous research where activity was used as the sole measurement include Firk et al. [2003b] and Roelofs et al. [2005]. Firk et al. [2003b] achieved sensitivity up to 94% but suffered an error ratio of 53%. The best results presented with respect to false alerts achieved 21% error ratio and a sensitivity of 71%. Results by Roelofs et al. [2005] showed sensitivity up to 87% with error ratio of 40%. In McGowan et al. [2007] the activity measure of the IceTag[®] and obtained sensitivity up to 92.9% with an error ratio of 17.0%, according to data from 21 days for 14 dairy cows.

Several authors have combined multiple traits in their detection algorithms in order to obtain better detection results, e.g. de Mol et al. [1997] and Firk et al. [2003a]. de Mol et al. [1997] combined measurements on activity, milk yield, milk temperature, electrical conductivity and concentrate leftovers. They achieved sensitivity up to 95% with a specificity of 94%. The specificity is the result of 1488 false alerts in 24219 inspections (inspections made twice a day). Their best results with respect to specificity was 98% (680 false alerts in 34863 inspections) combined with a sensitivity of 82.5%. Firk et al. [2003a] combined measurements on activity with period from last oestrus. When considering cows with and without information on previous oestrus cases, the result was a sensitivity of 88.9% and an error ratio of 23.8%. A very comprehensive study spanning 58
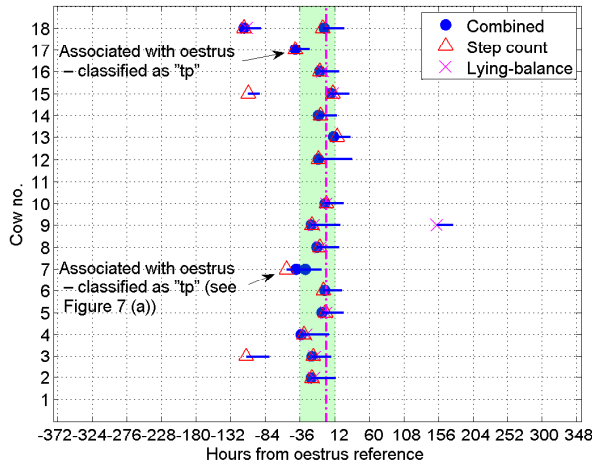
Figure D.6: Onset of oestrus alerts for the individual dairy cows plotted with respect to the oestrus reference and the period of valid detection. The duration of the alerts is shown with a solid line. The oestrus reference is plotted with a dash-dotted vertical line. The period of valid detection is shown as the shaded area.

dairy cows over 92 days by O'Connell et al. [2011] combined measurements of milk progesterone level and activity with sensitivity 71% and error ratio 14%. It should be emphasised that the numbers of different studies are not always comparable due to different selections and size of data-sets used.

With caution due to limited number of dairy cows in the study, the results have shown that very good detection ratios and in particular low false detection ratios can be obtained using the parameter adaptation and change detection techniques on the combined *lying-balance* and step-count measurements.

There is scope for additional improvements of the algorithms presented in this paper: The step counts were modelled using an exponential distribution, which was chosen for mathematical convenience. A better fit to data could be obtained using a gamma distribution. However, the gamma distribution has two parameters and this would make the optimisation process more involved. The lying balance has a natural probabilistic counterpart as the distribution function for the waiting time distribution for a change of state. If this is exploited, the functional form of the lying balance could be based on characteristics of the lying data. To facilitate such additional investigations, the algorithms are presented in algorithmic form in D.I and D.II

D.5 Conclusion

This paper has established change detection algorithms for detecting dairy cows in oestrus. The input variables to the algorithms are 1) a binary variable describing if a cow was mainly lying or not lying in a given time interval and 2) the number of steps taken by a cow in a given time interval. The time interval was taken to be 1 minute.

Specifically, the step counts were used in a detection algorithm which was designed to accommodate non Gaussian data. Furthermore, a lying balance was introduced as a biologically inspired quantity describing how much the cow has been lying during the preceding period. The input to this balance was the binary lying variable. A statistical change detection algorithm based on this balance was designed. Detection was investigated when combining the two statistical change detectors.

Both detection algorithms exploited knowledge of the expected intervals between oestruses and expected duration of oestrus and technicalities such as the known direction of change. A virtue of the algorithms is that they are based on on-line estimation of parameters for the individual animals. This is important from a practical point of view if an implementation of the algorithms in farm equipment is envisioned: There is no global set of parameters which are needed; instead the cow specific parameters are estimated on–line as data is observed.
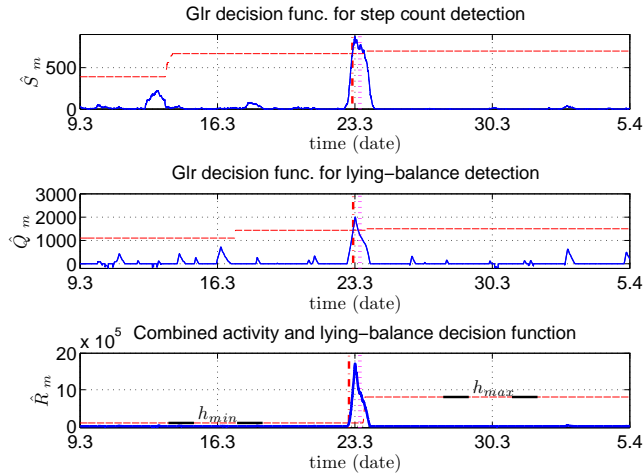
The results of the combined detector showed clearly improved performance, enhancing the number of successful alerts and significantly reducing the number of false positives.

D.6 Acknowledgements
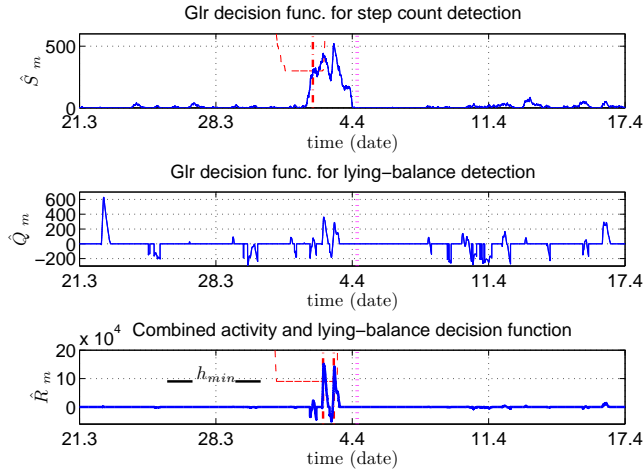
(a) Cow no. 7

(b) Cow no. 8

Figure D.7: Examples of detection results for two dairy cows using two sepa-
rate GLR detectors, on activity and lying-balance respectively,
combined using an exponentially weighted moving covariance.
The decision functions are shown with solid lines. The adaptive
threshold is shown with a dashed line where the h_{min} and h_{max}
are indicated with short solid lines. Oestrus alerts are shown with
dash-dotted lines and the reference for the insemination at 6 am
on the day of insemination is shown with a dotted line.

References

M. Basseville and I. V. Nikiforov. *Detection of Abrupt Changes: Theory and Application*. Information and System Science. Prentice Hall, New York, 1993.

M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki. *Diagnosis and Fault-Tolerant Control*. Springer, 2 edition, 2006.

U. Brehme, U. Stollberg, R. Holz, and T. Schleusener. Alt pedometer-new sensor-aided measurement system for improvement in oestrus detection. *Computers and Electronics in Agriculture*, 62(1):73–80, 2008. ISSN 01681699.

S. Chaudhari and Y. Sabo. Techniques for reproductive efficiency with reference to oestrus detection and timing of insemination in cattle. *Journal of Applied Sciences*, 6(10):2141, 2006. ISSN 18125654.

M. A. Crowe. Resumption of ovarian cyclicity in post-partum beef and dairy cows. *Reproduction in Domestic Animals*, 43(s5):20–28, 2008. doi: 10.1111/j.1439-0531.2008.01210.x.

R. M. de Mol and W. E. Woldt. Application of fuzzy logic in automated cow status monitoring. *Journal of Dairy Science*, 84(2):400–410, 2001.

R. M. de Mol, G. H. Kroeze, J. M. F. H. Achten, K. Maatje, and W. Rossing. Results of a multivariate approach to automated oestrus and mastitis detection. *Livestock Production Science*, 48(3):219–227, 1997.

R. M. de Mol, A. Keen, G. H. Kroeze, and J. M. F. H. Achten. Description of a detection model for oestrus and diseases in dairy cattle based on time series analysis combined with a kalman filter. *Computers and Electronics in Agriculture*, 22(2/3):171–185, 1999.

H. Dobson, S. L. Walker, M. J. Morris, J. E. Routly, and R. F. Smith. Why is it getting more difficult to successfully artificially inseminate dairy cows? *animal*, 2(08):1104–1111, 2008. doi: 10.1017/S175173110800236X.

W. J. Eradus and M. B. Jansen. Animal identification and monitoring. *Computers and Electronics in Agriculture*, 24(1/2):91–98, 1999.

W. J. Eradus, H. Scholten, and A. J. Udink-ten Cate. Oestrus detection in dairy cattle using a fuzzy inference system. *Control applications and ergonomics in agriculture CAEA ' 98: A Proceedings volume from the IFAC Workshop, Athens, Greece, 14 17 June 1998*, 1999.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Automation of oestrus detection in dairy cows: a review. *Livestock Production Science*, 75(3):219–232, 2002.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Improving oestrus detection by combination of activity measurements with information about previous oestrus cases. *Livestock Production Science*, 82(1):97–103, 2003a.

R. Firk, E. Stamer, W. Junge, and J. Krieter. Oestrus detection in dairy cows based on serial measurements using univariate and multivariate analysis. *Archiv fur Tierzucht*, 46(2):127–142, 2003b.

N. C. Friggens, M. Bjerring, C. Ridder, S. Højsgaard, and T. Larsen. Improved detection of reproductive status in dairy cows using milk progesterone measurements. *Reproduction in Domestic Animals*, 43(s2):113–121, 2008.

F. Gustafsson. *Adaptive Filtering and Change Detection*. John Wiley & Sons, Ltd, 2000.

D. Hawkins and E. Maboudou-Tchao. Multivariate exponentially weighted moving covariance matrix. *Technometrics*, 50(2):155–166, 2008. ISSN 00401706.

J. Hunter. The exponentially weighted moving average. *Journal of Quality Technology*, 18(4):203–210, 1986. ISSN 00224065.

R. I. Jónsson, T. Björgvinsson, M. Blanke, N. K. Poulsen, S. Højsgaard, and L. Munksgaard. Oestrus detection in dairy cows using likelihood ratio tests. In *Proceedings of the 17th World Congress, The International Federation of Automatic Control, Seoul, Korea, July 6-11, 2008*, 2008.

P. Liberati and P. Zappavigna. Improving the automated monitoring of dairy cows by integrating various data acquisition systems. *Computers and Electronics in Agriculture*, 68(1):62–67, 2009. ISSN 01681699.

X. Liu and S. L. Spahr. Automated electronic activity measurement for detection of estrus in dairy cattle. *Journal of Dairy Science*, 76(10):2906–2912, 1993.

N. Livshin, J. Grinshpun, L. Rpsenfeld, I. Shvartzman, A. Antler, B. Zion, G. Stojanovski, G. Bunevski, and E. Maltz. Lying behaviour of dairy cows under different housing systems and physiological conditions. *Precision Livestock Farming '05*, pages 305–311, 2005.

P. Løvendahl and M. Chagunda. On the use of physical activity monitoring for estrus detection in dairy cows. *Journal of Dairy Science*, 93(1):249–259, 2010. ISSN 00220302.

K. Maatje, R. M. de Mol, and W. Rossing. Cow status monitoring (health and oestrus) using detection sensors. *Computers and Electronics in Agriculture*, 16(3):245–254, 1997.

J. MacGregor. The exponentially weighted moving variance. *Journal of Quality Technology*, 25(2):106–118, 1993. ISSN 00224065.

J. McGowan, C. Burke, and J. Jago. Validation of a technology for objectively measuring behaviour in dairy cows and its application for oestrous detection. *Proceedings of the New Zealand Society of Animal Production*, 67:136–142, 2007.

A. S. Moore and S. L. Spahr. Activity monitoring and an enzyme immunoassay for milk progesterone to aid in the detection of estrus. *Journal of Dairy Science*, 74(11):3857–3862, 1991.

L. Munksgaard, C. G. Reenen, and R. Boyce. Automatic monitoring of lying, standing and walking behavior in dairy cattle. *Journal of Animal Science, Conference Supplement*, 84:304, 2006.

J. Neyman and E. S. Pearson. On the problem of the most efficient tests of statistical hypotheses. *Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character*, 231: 289–337, 1933. ISSN 02643952.

. O'Connell, F. Tøgersen, N. Friggens, P. Løvendahl, and S. Højsgaard. Combining cattle activity and progesterone measurements using hidden semi-markov models. *Journal of Agricultural, Biological, and Environmental Statistics*, 16: 1–16, 2011. ISSN 1085-7117.

J. B. Roelofs, F. J. C. M. van Eerdenburg, N. M. Soede, and B. Kemp. Pedometer readings for estrous detection and as predictor for time of ovulation in dairy cattle. *Theriogenology*, 64(8):1690–1703, 2005.

R. W. Rorie, T. R. Bilby, and T. D. Lester. Application of electronic oestrus detection technologies to reproductive management of cattle. *Theriogenology*, 57(1):137–148, 2002.

P. Trénel, M. Jensen, E. Decker, and F. Skjøth. Technical note: Quantifying and characterizing behavior in dairy calves using the icetag automatic recording device. *Journal of Dairy Science*, 92(7):3397–3401, 2009. ISSN 00220302.

H. A. Zarchi, I. Jónsson, R., and M. Blanke. Improving oestrus detection in dairy cows by combining statistical detection with fuzzy logic classification. In *Proceedings of the 7th Workshop on Advanced Control and Diagnosis*, 2009.

D.I   Algorithm for oestrus detection

The procedure for the oestrus detection is described in Algorithm D.1. The procedure for calculating the lying-balance is described in Algorithm D.2.

Algorithm D.1 Oestrus detection

Define:		Initial values:
		Distribution parameters,
		$\hat{\mu}^z_{0_0} = 0$, $\hat{\mu}^\gamma_{0_0} = 0.5$, $\hat{V}^\gamma_{0_0} = 0$
		Threshold parameters,
		$h_{min} = 9 \times 10^4$, $h_{max} = 8 \times 10^5$,
		$H = 23040$, $\upsilon = 1080$, $c = 3$.
		Detection parameters,
		$\lambda_\mu = \lambda_\upsilon = 0.0001$, $\lambda_r = 0.995$,
		$U = 1440$, $L = 720$.
Init:		set $m = 1$
Loop:		
	1.	observe the step count z_m.
	2.	calculate $\hat{\gamma}_m$ using Algorithm D.2.
	3.	calculate $\hat{\mu}^z_{0_m}$ (5), $\hat{\mu}^\gamma_{0_m}$ (5), $\hat{V}^\gamma_{0_m}$ (15).
	4.	calculate $\hat{S}_m$ (6), $\hat{Q}_m$ (16) and $\hat{R}_m$ (18).
	5.	If $m > H + \upsilon$
	5a.	calculate h_m (19).
	5b.	if $\hat{R}_m \geq h_m$ issue oestrus alert.
	5c.	if $\hat{R}_m \leq h_m \times 0.01$ reset alert.
	6.	$m := m + 1$ continue with step 1.

D.II   Algorithm for lying-balance

The procedure for calculating the lying-balance is described in Algorithm D.1.
The initial values are set to $\hat{\gamma}_0 = 0.5$, $\mu_0^l = \mu_0^s = 12 \times 24 \times 60$ and $T_0 = 0$.

Algorithm D.2 Lying-balance calculation

Define:	Initial values:
	Estimation of model,
	$T_0 = 0$, $\lambda = 0.99$, $\mu_0^l = \mu_0^s = 144$
	Lying-balance,
	$\hat{\gamma}_0 = 0.5$
Init:	set $m_c = 0$, $m = 1$, observe the
	lying/standing state y_m and set $y_0 = y_m$,
	calculate Eq. (12) and
	determine κ from Eq. (13)

Loop:

1   observe the lying/standing state y_m.
2   if $y_m \neq y_{m-1}$, set
$m_c = m - 1$,
$\mu_{m_c}^l = \mu_{m-1}^l$,
$\mu_{m_c}^s = \mu_{m-1}^s$
3   calculate κ from Eq. (13)
4   calculate μ_m^l, μ_m^s Eq. (12)
5   calculate the lying-balance γ_m using
6   Eq. (10).
7   $m := m + 1$ and continue with step 1.

On-line detection of lameness in dairy cows[1]

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Abstract

Observations of behavior are used to detect lameness in dairy cows. The aim is to enable an automatic lameness detection using only behavioral observations that are obtainable using low-cost sensors. Manual observations on cows' lameness state were available with approximately two weeks interval. These observations are taken to be the "truth". Sensors used are monitoring activity, eating behavior and milking behavior. Visits to feeding bins were aggregated into meals using earlier published methods. A maximum likelihood classification was used to classify the observations of behavior into the two classes, lame or not lame. The variables used in the classification were 1) activity; 2) number of visits to feeding bins; 3) duration of visits to the feeding bins; 4) number of meals; 5) duration of meals; 6) feed intake; 7) feed intake rate and 8) number of visits to the milking robot. A key component was the aggregation of the variables over time intervals. The classification was tested using different combinations of these variables aggregated over different time intervals and data records from days where manual lameness observations were made. The new classification algorithm employed estimated posterior probabilities of several days prior to each manual observation to enhance the probability of detection and to reduce

the probability of false alarms. Results showed that 72.4% of the lameness cases were detected, with an associated specificity of 72.1%, using only the number of meals within an interval and the duration of meals within an interval. Adding activity, feed intake and visits to milking robot, improved results to the extent that 75.5% of lameness cases were detected with a specificity of 73.5%.

E.1 Introduction

From an animal welfare as well as an economical perspective, detection of lameness is important in modern dairy production. Lameness can result in pain or discomfort (Beusker [2007]), and is associated with reduced yield (Hernandez et al. [2005]). Furthermore, lameness is related to poorer reproduction, costs of treatment (Ettema and Østergaard [2006]) and higher probability of cows being culled (Booth et al. [2004]). With growing farm sizes, dairy farmers often fail to detect lame cows (Whay et al. [2003]). Therefore, there is a need for development of methods for automatic lameness detection. Several approaches for detection of lameness have been reported in the literature: Mazrier et al. [2006] use activity measurements, Pastell et al. [2008] use force sensors and Chapinal et al. [2009] use changes in walking speed and lying behavior. There is evidence that changes in short-term feeding behavior of dairy cows are related to lameness (Gonzalez et al. [2008]), and Kramer et al. [2009] developed a fuzzy logic model for classification of lameness based on milk yield, dry matter intake, number of visits at the feeding trough, time spent at the feeding troughs, water intake, activity and preliminary cases of lameness in the actual lactation. They reported that the algorithm was able to detect 72.7% of the lameness cases with specificity of 75.9%. However, Kramer et al. [2009] used the total number of visits to the feeders and it is likely that the number of meals rather than the number of visits is affected by lameness. The relation between meals and visits is discussed in Tolkamp et al. [2000].

E.2 Materials and methods

E.2.1 Housing and animals

Data were collected from in total 173 lactating Holstein cows over a period of 32 months. The cows were kept in a loose housing system with free stalls and slatted floors on the Danish Cattle Research Centre (Tjele, Denmark) in two groups with approximately 53 cows in each group. Each group had access to an automatic milking system (DeLaval, Tumba, Sweden). Activity was measured by means of commercial activity tags (ALPRO by DeLaval) placed on the cows collar. The cows had ad libitum access to a mixed ration, however, the composition of the feed varied over time and between cows. There were in average 0.5 feeding bins per cow. If a cow was moved to an area without free access to the milking robot while in lactation, data from that period was discarded in the analysis.

E.2.2 Data recording and calculation of variables

Lameness scores were made once every other week by trained observers when the cows were walking on the slatted floor in the barn according to the method described by Thomsen et al. [2008]. The scoring system is a 5-level gradual system where score 1 means no signs of lameness and score 5 means severe sign of lameness. Lameness observations were made on 154 different days during the period of collection of data. Data included 173 cows and the cows were scored on average 21 times (range 1-48). The analysis included a total of 3638 lameness scores. The 5 categories were aggregated into two categories, partly to simplify the analysis and partly because there were very few cows with lameness score 5. We considered two aggregations, namely $c_1 = [1, 2, 3]$, $c_2 = [4, 5]$ and $c_1 = [1, 2]$, $c_2 = [3, 4, 5]$.

Eating behavior and feed intake were obtained from the Insentec monitoring system (Insentec, Marknesse, the Netherlands), and activity data and recordings of milk yield and total number of visits to the robot were collected from the DeLaval system (DeLaval, AB, Tumba, Sweden). Frequency and duration of meals were calculated according to the methods of Tolkamp et al. [2000] and Yeates et al. [2001]. For a more detailed description of the analysis of the intervals between visits, see Appendix E.I. Feed intake rate is defined as the total feed intake in a specified time window divided by the time spent at the feeding bin during the specific time window (the choice of the time window is discussed later). The calculation of the intake rate was based on raw data on duration of visits to the feeding bins and not the calculated duration of meals.

To assess the effect of aggregation, each variable was summed over 4 h intervals and then we made an analysis of variance with the interval and lameness score as factors (where lameness score was aggregated as $[1, 2]$, $[3]$ and $[4, 5]$). This is discussed in Section E.5.1.

E.2.3 Classification

At each day we have recordings of 1) activity Act_t; 2) the number of visits to the feeders or feed bins nV_t; 3) the duration of visits to the feeding bins dV_t; 4) the number of meals nM_t; 5) the duration of meals dM_t; 6) the feed intake wI_t; 7) the feed intake rate rI_t and 8) the number of visits to the milking robot $nMilk_t$. These variables were aggregated into a vector which we generically denote by X_t (details of this aggregation are described below). Based on the vector we classified a cow as belonging to either of the two groups normal (group c_1) or lame (group c_2) using maximum likelihood classification based on linear

discriminant analysis (LDA), see e.g. Seber [2004]. The probability that a sample X_t comes from class c_j (for $j = 1,\ 2$) is

$$P(c_1|\mathbf{X}_{t-d}) = \frac{p_1 f_1(\mathbf{X}_{t-d})}{p_1 f_1(\mathbf{X}_{t-d}) + p_2 f_2(\mathbf{X}_{t-d})}, \tag{1}$$

where $f_1(x)$ and $f_2(x)$ are probability density functions for multivariate normal distributions $N(\mu_1, \Sigma)$ and $N(\mu_2, \Sigma)$ and p_1, p_2 are the prior probabilities of the normal and the lame groups c_1 and c_2 (in this study we have taken $p_1 = p_2 = 0.5$). Based on the vector X_t, a cow is assigned to the class with the highest probability. It has been found empirically that the probability of correct classification could be improved by not only using variables measured on the day of scoring but also on the days just before scoring. We aggregate the logarithm of the posterior probabilities over $d + 1$ days up to and including the day of scoring as

$$Q_t(c_1|t-1) = \sum_{i=t-d}^{t-1} \log(P(c_1|\mathbf{X}_i)) \tag{2}$$

Based on this sequence a cow is assigned to the class for which $Q_t(c_j)$ is largest. Choices of d are discussed below.

E.3   Validation

For a given set of variables the unknown parameters were μ_1, μ_2 and Σ were estimated as follows. For each cow we estimated these parameters based on data from all other cows. Then for each day of scoring we classified the state of the cow using $Q_t(c_j)$ as defined above.

E.4   Variable selection

A critical aspect of our method is the variable selection which comprises 1) a choice of which of the variables to be used in the classification 2) choices about aggregation of each variable into time windows of different lengths and 3) choice of number of days prior to the day of manual observation d for which data should be used.

For some variables a 24 h aggregation might be most suitable and for others a shorter aggregation period may be better. Activity, for example, is always lower at night than during the day independently of whether a cow is lame or not. If

a lame cow has lower activity than a healthy cow during the day but not during the night then activity should be aggregated into shorter time windows so that day-time differences between lame and healthy cows are not obscured by overall low activities during night time. For most behavioral traits the behavior was assumed to vary during the day and therefore an aggregation period of 4, 6 or 8 h would capture the diurnal variation in the behavior. However, for the intake rate rI_t and the number of visits to the milking robot $nMilk_t$ a strong diurnal variation was not expected. Therefore, these variables were summed over 24 h.

When using 6 intervals, the recordings each day were aggregated into the intervals $[00;04[$, $[04;08[,\ldots$, $[20;24[$ and when using 3 intervals the recordings were aggregated into the intervals $[00;08[$, $[08;16[$, $[16;24[$. We use the notation ^6nM_t to indicate that nM_t has been aggregated into 6 intervals of 4 h and so on so that, for example, $X_t = [^6nM_t^3dM_t]$ is a vector with $6 + 3 = 9$ elements. Notice: If a full 24 h period is used, we write nM_t instead of ^1nM_t.

During the classification test, all combinations of the variables mentioned above were tested, ranging from using only 1 of the variables up to using all 8 variables. For each variable included, different durations of aggregation were tested. For the variables 1) activity; 2) feed intake; 3) number of visits to the feeding bins; 4) duration of visits to the feeding bins; 5) number of meals and 6) the duration of meals, the day was split into 1, 2, 3 and 6 intervals (24 h, 12 h, 8 h, and 4 h aggregation). The rate of feed intake and the number of visits to the milking robot were tested using only a 24 h aggregation. For each combination of variables the number of days prior to the day of manual observation d ranged from 0 to 1. There are about 125,000 combinations of these. For each combination j we applied the validation scheme described above and calculated sensitivity and specificity. To obtain the overall performance as a single number we weighted sensitivity (SEN) and the specificity (SPE) differently and calculated $\alpha\text{SEN}_j + (1-\alpha)\text{SPE}_j$. In order to demonstrate the effects of the weighting between the sensitivity and the specificity the best results using varying values of the weighting factor α and the best results for different values of α are presented. The best results for each value of α were found by choosing the maximum of this sum.

E.5   Results

This section first summarizes the data and then describes the performance of the classification algorithm.

E.5.1 Observations of behavior

Figure E.1 shows the estimated mean values and standard deviations of daily values of the variables (summed over 24 h). Only observations recorded on days where lameness scores were recorded were included in the analysis.

On a 24 h basis lame cows visited the feeders less often and the duration of eating decreased with increasing score for lameness, whereas the intake rate increased. The difference between lame and non-lame cows in feed intake, number of visits to the robot and level of activity was less clear. However, there was a large variation between cows in all variables. Although cows with high lameness score had fewer and shorter meals the difference between the categories of cows with different lameness score differed during the day. There was no significant difference in the mean number of meals and the duration of meals during the evening; whereas the largest numerical difference was found in the morning (8 to 12) and afternoon (16 to 20). Cows with lameness score 3 and cows with lameness score 4 and 5 differed from cows with lameness score 1 and 2 in these periods (P < 0.01) (Figure E.2). During midday and night, the feed intake did not differ between cows with different lameness score. However, lame cows were eating less in the afternoon and more during the evening compared to non-lame cows (Figure E.3).

E.5.2 Detection results

The classification results varied considerably depending on which variables were included in the analysis and on the selected weighting factor α, that determines the ratio between the sensitivity and specificity when searching for the best results. The sensitivity and specificity when each variable was used individually in a classifier in the form of 24 h aggregated time-history data were all relatively low (Table E.1). Table E.2 shows the combination of variables that resulted in the best results using the values of the weighting factor $\alpha = 0.3,\ 0.5,\ 0.7$ and 0.9. The diurnal variation was described by splitting data into a number of segments within each 24 h period. This is shown in Table E.2 as a pre-superscript to the variable. With Act_t denoting activity, $^3Act_t$ indicates that a 24 h record of activity is sliced to cover the day over three consecutive intervals. In general, both sensitivity and specificity was higher when based on a combination of variables. Notice that treating cows with score 3 as being non-lame leads to increased sensitivity and specificity. (rightmost column of Table E.1 and E.2). The upper part of Table E.2 shows the best results including all combinations of variables. In the mid-lower part the feed intake (wI_t) and feed intake rate (rI_t) were excluded such that only traits that can be measured using low-cost measuring

Table E.1: Classification results using records of activity (Act_t), number of visits to the feeders or feed bins (nV_t), duration of visits to the feeding bins (dV_t), number of meals (nM_t), duration of meals (dM_t), feed intake (wI_t), feed intake rate (rI_t) and number of visits to the milking robot $(nMilk_t)$. All results are given using $d = 1$ (see equation (2)) and aggregating time-history data over 24 h. The results are shown in form of sensitivity (SEN) and specificity (SPE.).

X_t	$c_1 = [1, 2]$ $c_2 = [3, 4, 5]$ SEN %	SPE %	$c_1 = [1, 2, 3]$ $c_2 = [4, 5]$ SEN %	SPE %
$\begin{bmatrix}Act_t\end{bmatrix}$	55.0%	48.8%	54.1%	48.8%
$\begin{bmatrix}nV_t\end{bmatrix}$	63.8%	49.1%	71.4%	55.0%
$\begin{bmatrix}dV_t\end{bmatrix}$	58.8%	56.7%	66.3%	66.2%
$\begin{bmatrix}nM_t\end{bmatrix}$	60.9%	52.9%	59.2%	63.5%
$\begin{bmatrix}dM_t\end{bmatrix}$	58.3%	56.3%	70.4%	66.0%
$\begin{bmatrix}wI_t\end{bmatrix}$	54.3%	51.5%	46.9%	53.2%
$\begin{bmatrix}rI_t\end{bmatrix}$	55.2%	66.1%	67.4%	74.9%
$\begin{bmatrix}nMilk_t\end{bmatrix}$	66.9%	43.7%	65.3%	42.0%

equipment were included. The last row shows which results are achievable using only the number of meals (nM_t) and the duration of meals (dM_t). The combination of variables that lead to the best classification results are obtained using $d = 1$ (see equation (2)).

E.6　Discussion

The results suggest that it was difficult to distinguish between lame and none lame cows when cows with lameness score 3 were included in the group of lame cows; neither sensitivity nor specificity reached 70.0%. Better detection results were obtained when separating cows with lameness scores 4 and 5 from cows with lameness scores 1, 2 and 3. In that case the best results were at a sensitivity of 75.5% and a specificity of 73.5% when activity, number of meals, duration of meals, feed intake and number of visits to the milking robot, all within a time window, were included in the calculations. This suggests that the behavior and feed intake of cows with lameness score 3 are more similar to normal behavior than the behavior of more severely lame cows. Lame cows spent less time eating and with fewer bouts. However, the rate of feed intake increased, thus the feed intake did not differ per day even though there were differences in the diurnal

rhythm of the feed intake.

A sensitivity of 72.4% and a specificity of 72.1% could be gained using only the number of meals and the duration of meals within a time window. This result is of potential practical importance if low-cost sensors of eating time become available.

The behavior of dairy cows is affected by a large number of both intrinsic and extrinsic factors (Rushen et al, 2008). Thus, it is not surprising that detection of lameness based on only one variable showed rather poor detection accuracy. However, the classification model quite accurately predicted when cows were lame based on information about number of meals and meal duration when the diurnal variation in number of meals was included in the model. During the evening and night the difference in eating behavior between lame and non lame cows were less obvious. Although the diurnal rhythm in eating behavior will vary between farms and therefore the optimal choice of intervals may vary between farms, our results suggest that prediction of lameness should be based on recordings done during the active periods. However, the lame cows had an increased feed intake during the evening in contrast to the rest of the day where the feed intake was lower or did not differ from none-lame cows. Furthermore, the results suggest that lame cows compensate by increasing the rate of eating. However, further studies are needed to verify the diurnal rhythm in eating behavior and feed intake of lame and none-lame cows.

The sensitivity and especially the specificity were improved when information about feed intake was included and the results are in line with a previous study (Kramer et al. 2009). Kramer et al. (2009) included information about feed intake and "information about preliminary diseases in the actual lactation". However, feed intake and precise information about previous lameness cases may be more difficult to obtain under commercial conditions than eating behavior.

There is some evidence that lameness is related to a lower number of visits to the milking unit (Borderas et al. 2008). Our results are in agreement, but the number of visits to the milking unit were a rather poor predictor of lameness and the specificity was low. Therefore, detection of lame cows did not improve by including the number of visits. In our study, the measure of the level of activity was based on data from a sensor placed on the neck of the cow. The results suggest that such a measure of activity do not add much to the detection of lameness properly because the activity level also reflects some movements that are not related to the gait of the cow. However, it is likely that a sensor placed on the leg may provide more accurate information about the gait of cows and thus can improve the detection. On a smaller number of cows Chapinal et al. (2011) demonstrated that measures of acceleration were correlated to gait scores and visually assessed asymmetry of the steps when the accelerometers were attached

to the legs.

We chose the maximum likelihood classification as the detection method because it is easily implemented in hardware. Furthermore, with this method it is possible to weight the sensitivity and the specificity differently. Hence, one might decide that it is better to get too many alarms than it is to miss a lameness case.

The approach has the limitations, if looking to commercial use, that there is not certainty that the values determined for the classification will be optimal for other farms. Other farms may have different diurnal rhythms and the best values for the classification could well be different between farms. It is therefore likely that the algorithm would have to be adaptive. The equipment could use some initial values for the discrimination but there would have to be some sort of a calibration including information about actual lameness on the farm.

E.7 Conclusion

None of the variables or combinations of the variables activity and visits to milking robot showed sufficient accuracy in detection of lame cows. This study showed promising results on lameness detection based on recordings that in near future may be obtained using only low-cost sensor equipment. A key element in our strategy was the aggregation of data into time intervals of appropriate lengths. Further studies need to be conducted to reveal whether the time intervals are farm specific, moreover, it needs to be investigated whether the parameters, which were estimated in this study, are applicable on other farms.

E.8 Acknowledgements
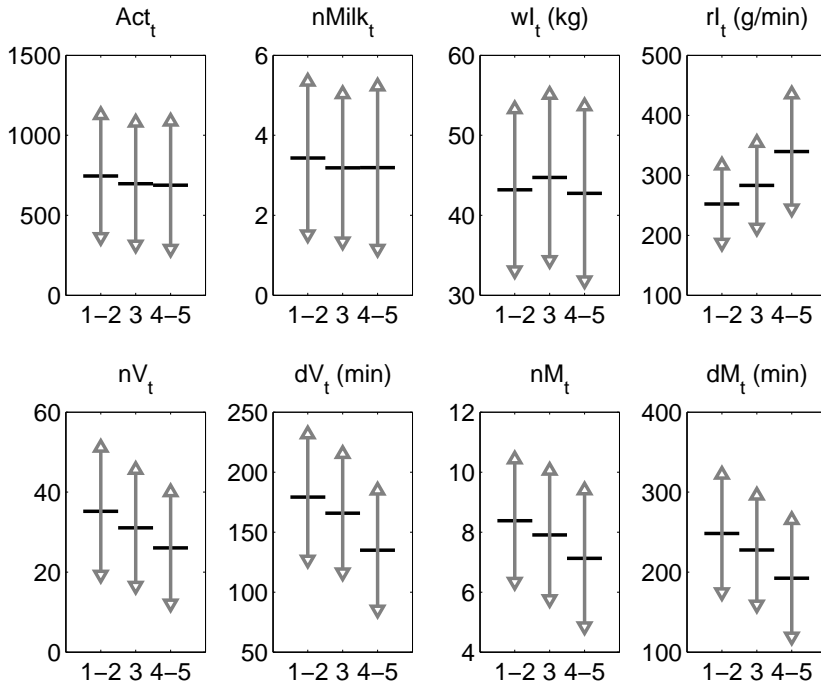
Figure E.1: Estimated mean values and standard deviations of behavior and feed intake versus lameness score. All values are summed over 24 h. Lameness scores are divided into 3 groups: Normal (score = [1, 2]), mild lameness (score = 3) and lame state (score = [4,5]). The lameness scores are indicated on the x-axis. The plotted variables are activity (Act_t), number of visits to the milking robot $(nMilk_t)$, feed intake (wI_t), feed intake rate(rI_t), number of visits to the feeders or feed bins (nV_t), duration of visits to the feeding bins (dV_t), number of meals (nM_t) and duration of meals (dM_t).
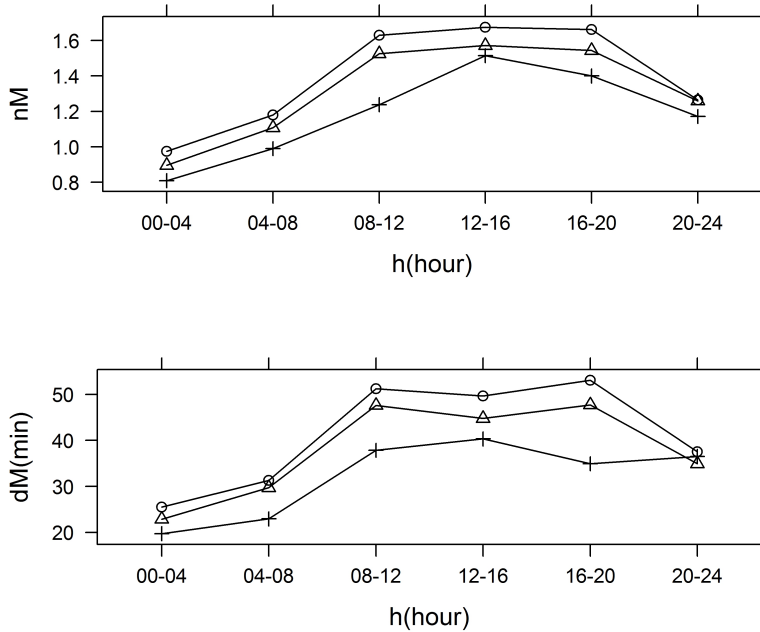
Figure E.2: Estimated mean values of the aggregated number of meals (nM_t) and the aggregated duration of meals during the day (dM_t), split into 6 intervals (h is the hour of the day). Lameness scores = [1; 2] are indicated with a circle, scores = 3 with a bin and scores = [4; 5] with a cross. Plot (a) shows the estimated mean values of number of meals and plot (b) the estimated mean values of the duration of meals. The estimated standard deviation of the number of meals per day when aggregating over 4 h was found as SD = 0.8. For the mean of duration of meals the standard deviation was SD = $31min$.
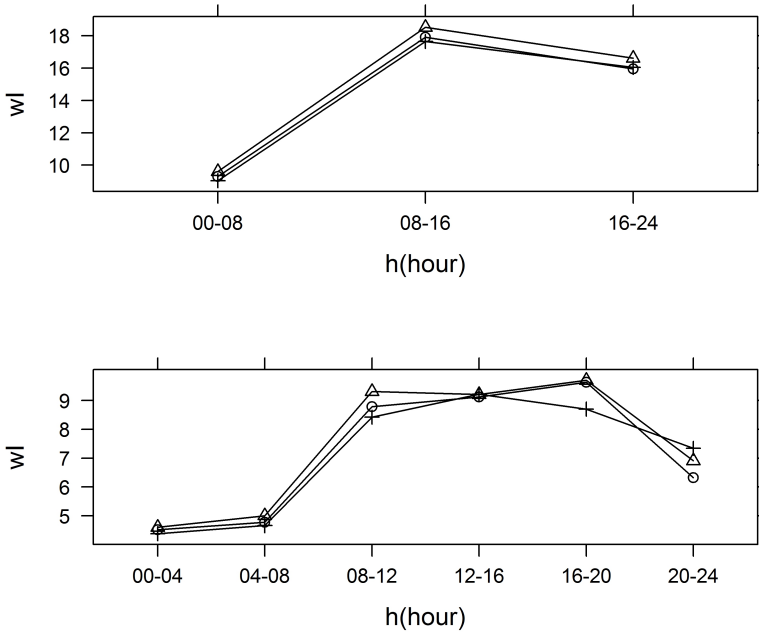
Figure E.3: Estimated mean values of the aggregated feed intake during the day (wI_t), aggregated into 3 and 6 intervals, respectively, where (h is the hour of the day). Lameness scores = [1; 2] are indicated with a circle, scores = 3 with a bin and scores = [4; 5] with a cross. Plot (a) shows the estimated mean values of the normal and lame behavior during the day split into 3 intervals and plot (b) into 6 intervals. The standard deviation of the feed intake when aggregating over 8 h was found to be SD = 6.7 kg. When aggregating over 4 h the estimated standard deviation was SD = 4.9 kg.

Table E.2: Best classification results combining variables using different values of the weighting factor α. The values used are α = 0.3, 0.5, 0.7 and 0.9. The combination of variables and number of segments within each 24 h period were found treating cows with score 3 as being non-lame. The included variables are, activity (Act_t), number of visits to the feeders or feed bins (nV_t), duration of visits to the feeding bins (dV_t), number of meals (nM_t), duration of meals (dM_t), feed intake (wI_t), feed intake rate(rI_t) and number of visits to the milking robot ($nMilk_t$). The upper part of the table shows results where all variables are included. Records of feed intake and feed intake rate are excluded in the mid-lower part to indicate which results are achievable using only low cost sensors. The last row shows which results can be obtained using only the number and duration of meals. All results are given using d = 1 (see equation (2)). The results are given as sensitivity (SEN) and specificity (SPE.).

α	X_t	$c_1 = [1,2]$ $c_2 = [3,4,5]$ SEN %	SPE %	$c_1 = [1,2,3]$ $c_2 = [4,5]$ SEN %	SPE %
0.3	$[^2Act_t \quad ^6nV_t \quad ^2dV_t \ldots$ $^3nM_t \quad ^3dM_t \quad ^2wI_t \quad rI_t]$	55.5	66.9	65.3	83.4
0.5	$[^3Act_t \quad ^6dV_t \quad ^2nM_t \ldots$ $^2dM_t \quad rI_t \quad nMilk_t]$	55.5	66.4	70.4	78.6
0.7 and 0.9	$[^3Act_t \quad ^3nM_t \quad ^6dM_t \ldots$ $wI_t \quad nMilk_t]$	60.6	60.5	75.5	73.5
0.3	$[^3Act_t \quad ^3nM_t \quad ^3dM_t \ldots$ $nMilk_t]$	55.0	61.2	69.4	74.9
0.5 and 0.7	$[^3nM_t \quad dM_t \quad nMilk_t]$	57.1	61.7	72.4	72.2
0.9	$[^2Act_t \quad ^2nV_t \quad ^2dM_t]$	58.9	56.0	73.5	67.7
0.9	$[^3nM_t \quad dM_t]$	57.6	62.0	72.4	72.1

References

N. Beusker. *Welfare of Dairy Cows: Lameness in Cattle - A Literature Review.* PhD thesis, Tierärztliche Hochschule Hannover, 2007.

C. J. Booth, L. D. Warnick, Y. T. Grohn, D. O. Maizon, C. L. Guard, and D. Janssen. Effect of lameness on culling in dairy cows. *Journal of Dairy Science*, 87(12):4115–4122, 2004. ISSN 00220302.

N. Chapinal, A. M. de Passille, D. M. Weary, M. A. G. von Keyserlingk, and J. Rushen. Using gait score, walking speed, and lying behavior to detect hoof lesions in dairy cows. *Journal of Dairy Science*, 92(9):4365–4374, 2009. ISSN 00220302.

J. F. Ettema and S. Østergaard. Economic decision making on prevention and control of clinical lameness in danish dairy herds. *Livestock Science*, 102(1-2): 92–106, 2006. ISSN 18711413.

L. A. Gonzalez, B. J. Tolkamp, M. P. Coffey, A. Ferret, and I. Kyriazakis. Changes in feeding behavior as possible indicators for the automatic monitoring of health disorders in dairy cows. *Journal of Dairy Science*, 91(3): 1017–1028, 2008. ISSN 00220302.

J. A. Hernandez, E. J. Garbarino, J. K. Shearer, C. A. Risco, and W. W. Thatcher. Comparison of milk yield in dairy cows with different degrees of lameness. *Journal of the American Veterinary Medical Association*, 227(8): 1292–1296, 2005. ISSN 00031488.

E. Kramer, D. Cavero, E. Stamer, and J. Krieter. Mastitis and lameness detection in dairy cows by application of fuzzy logic. *Livestock Science*, 125(1): 92–96, 2009. ISSN 18711413.

H. Mazrier, S. Tal, E. Aizinbud, and U. Bargai. A field investigation of the use of the pedometer for the early detection of lameness in cattle. *Canadian Veterinary Journal*, 47(9):883, 2006. ISSN 00085286.

M. Pastell, M. Kujala, A.-M. Aisla, M. Hautala, V. Poikalainen, J. Praks, I. Veermäe, and J. Ahokas. Detecting cow's lameness using force sensors. *Computers and Electronics in Agriculture*, 64(1):34–38, 2008. ISSN 01681699.

G. A. F. Seber. *Multivariate Observations.* John Wiley & Sons, Inc., Hoboken, NJ., 2004.

P. T. Thomsen, L. Munksgaard, and F. A. Tøgersen. Evaluation of a lameness scoring system for dairy cows. *J. Dairy Sci.*, 91(1):119–126, 2008.

B. J. Tolkamp, D. P. N. Schweitzer, and I. Kyriazakis. The biologically relevant unit for the analysis of short-term feeding behavior of dairy cows. *Journal of Dairy Science*, 83(9):2057–2068, 2000. ISSN 00220302.

H. R. Whay, D. C. J. Main, L. E. Green, and A. J. F. Webster. Assessment of the welfare of dairy cattle using animal-based measurements: direct observations and investigation of farm records. *Veterinary Record - English Edition*, 153 (7):197, 2003. ISSN 00424900.

M. P. Yeates, B. J. Tolkamp, D. J. Allcroft, and I. Kyriazakis. The use of mixed distribution models to determine bout criteria for analysis of animal behaviour. *Journal of Theoretical Biology*, 213(3):413–425, 2001. ISSN 00225193.

E.I Selecting length of intervals between meals

Methods for finding the time limit to distinguish between measurements that should be interpreted to indicate a short interruption in a meal to those showing an interval between two meals are based on analyzing the length of intervals between visits (from now on T_v) and the logarithm of the length of intervals between visits (from now on $\ln(T_v)$). Tolkamp et al. [2000] and Yeates et al. [2001] used a model of the distributions of $\ln(T_v)$ based on the hypothesis that the intervals could be split into three classes. The shortest intervals represented a behavior where the cow took her head out of the bin without ending the meal and put her head into a feeding bin shortly afterwords to continue the meal. The medium length intervals were water intervals where the cow walked to the water stand and drinked. Finally, the longest intervals represented intervals between two meals. Tolkamp et al. [2000] modeled the distribution for $\ln(T_v)$ as a Gaussian mixture model with 2 and 3 components and in Yeates et al. [2001], the distribution was modeled as a mixture of Gaussian and Weibull distributions. The 2-component model was used for cows that apparently did not take a water interval during the meal. The threshold between intervals belonging to intervals in a meal and intervals between two meals was found as the back-transformed value where the two distributions with the largest mean values intersected. A histogram of $\ln(T_v + 1)$ of the feeding data from this study at DCRC, pooled for all Holstein cows, together with the estimated normal density curve of a 3 compound mixture is shown in Figure E.4.

The intersection of the two distributions with the largest mean values is found at $T_v = 44.0$min. The corresponding value in the study of Yeates et al. [2001] was $T_v = 49.5$min. Using that same dataset, Yeates et al. [2001] found that
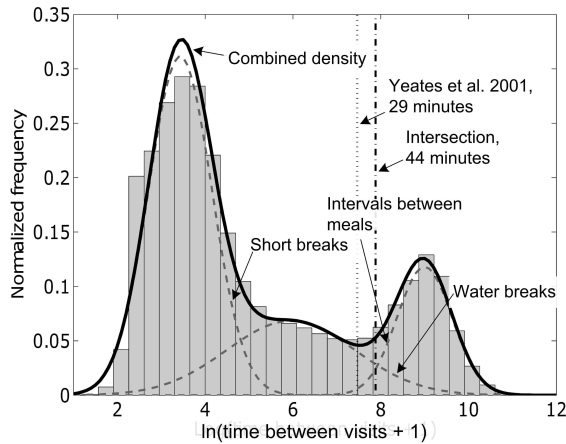
Figure E.4: Histogram of the pooled data of $\ln(T_v + 1)$ for the Holstein cows. On top of the histogram is plotted an estimated Gaussian mixture distribution with 3 components with a solid line. A distribution for each of the 3 components is plotted with a dashed line. The intersection of the two distributions with the largest mean values is shown with a dash-dotted line and the meal criterion found by Yeates et al. [2001] at $ln(29\text{min} + 1)$ is shown with a dotted line.

using a mixture of a Gaussian and two Weibull distributions, the intersection was at $T_v = 29.0$min. Using the $T_v = 49.5$min criterion gave 5.6 meals per day and using this value for seperation gave 6.1 meals per day. For the cows not considered to be taking a "water break" during the meals, Yeates et al. [2001] found the meal criterion to be $T_v = 22.2$min with 5.9 meals per day. In this study, the intersection of the two distributions with the largest mean values was found to be $T_v = 44$min, with a clear indication of a middle component describing a water break. The mean number of meals per day was found to be 7.1, which is a bit more than the 5.6 value that Yeates et al. [2001] estimated. As in the case of Yeates et al. [2001] using a mixture of three Gaussian distributions might lead to classifying a bit too many of the actual intervals between meals as water breaks. Using the $T_v = 29.0$min found in Yeates et al. [2001] instead increases the mean value of the number of meals to 7.9 which is similar to the increase in the number of meals experienced by Yeates et al. [2001]. The meal criterion for this study was therefore selected as 29.0 min.