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Oestrus Detection in Dairy Cows Using Likelihood Ratio Tests

Ragnar I. Jónsson * **Trausti Björgvinsson** * **Mogens Blanke** *
Niels K. Poulsen ** **Søren Højsgaard** *** **Lene Munksgaard** ****

* *Department of Electrical Engineering, Automation, Tech. Univ. of Denmark, Denmark,* `e-mail: rij@elektro.dtu.dk, mb@elektro.dtu.dk`
** *Department of Informatics and Math. Modelling, Tech. Univ. of Denmark, Denmark,* `e-mail: nkp@imm.dtu.dk`
*** *Institute of Genetics and Biotechnology, University of Aarhus, Denmark,* `e-mail: sorenh@agrsci.dk`
**** *Institute of Animal Health, Welfare and Nutrition, University of Aarhus, Denmark,* `e-mail: Lene.Munksgaard@agrsci.dk`

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 outperform earlier approaches in respect to combined statistics of false alarms and missed detections.

Keywords: animal husbandry; developments in measurement, signal processing; fault diagnosis and monitoring.

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. Schlunsen 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.

1. 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 and 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 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[h] window that has the greatest activity sum in a 48[h] space around the day of insemination. This is found by evaluating

Table 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

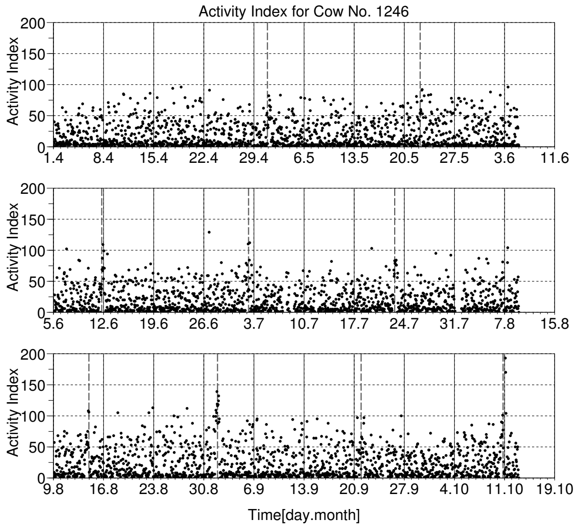

Fig. 1. Activity index for cow no. 1246.

$$k_{ot} = \underset{k_r - 24 \leq j \leq k_r + 24}{\arg\max} \sum_{i=j-\frac{24}{2}}^{j+\frac{24}{2}} y(i) \qquad (1)$$

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 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, Fig. 1 shows a plot of the activity data 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 Fig. 2. The histogram shows that the activity data are right skewed with considerable point mass in zero. Hence, a transformation, e.g. a logarithmic transforma-

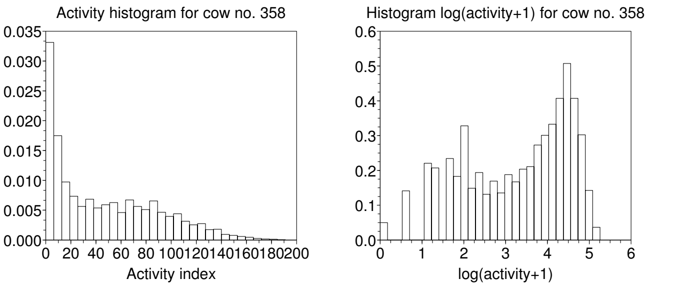

Fig. 2. Activity histogram and histogram of $\log(activity+1)$ for cow no. 358.

tion, of data does not produce normally distributed data either (see Fig. 2).

2. 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 2.1 and the derivation of the change detection algorithm is described in 2.2.

2.1 Residual Generator

Because cows move around, rest, eat, sleep, interact with other individuals and 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.

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. Fig. 3 shows the power spectrum of the activity for cow no. 358.

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

$$y(k) = \mu + A_1\cos(\omega_1 k) + B_1\sin(\omega_1 k) + \dots \qquad (2)$$
$$+A_m\cos(\omega_m k) + B_m\sin(\omega_m k) + \varepsilon(k)$$

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

$$\mathbf{Y} = \mathbf{\Phi}\theta + \varepsilon \qquad (3)$$

where

$$\mathbf{\Phi} = [1\ \cos(\omega_1 k)\ \sin(\omega_1 k)\ \dots\ \cos(\omega_m k)\ \sin(\omega_m k)] \qquad (4)$$

and

$$\theta^T = [\mu\ A_1\ B_1\ \dots\ A_m\ B_m] \qquad (5)$$

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

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

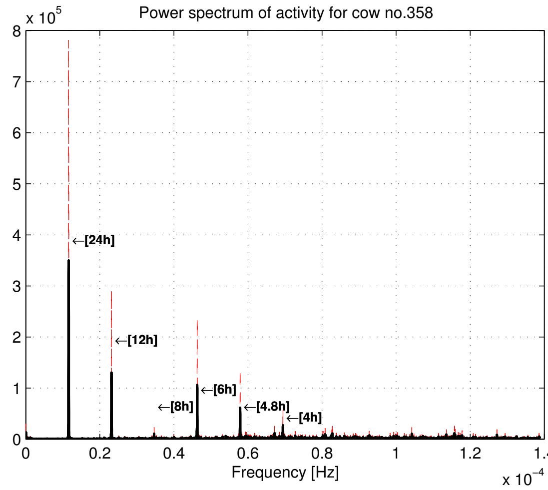

Fig. 3. Power spectrum of activity for cow no. 358.

This leaves us to the residual

$$\hat{\varepsilon} = \mathbf{Y} - \phi\hat{\theta} \qquad (7)$$

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

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

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

$$g > f^F_{1-\alpha}(n_b - n_a, N - n_b) \qquad (9)$$

where $f^F_{1-\alpha}$ 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 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 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[h] and 4[h]. 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

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

$\hat{\hat{g}}$	$\hat{\sigma}_g$	Quantile	$\frac{n_{sign.}}{n_{cows}}$	n	T[h]
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

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

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

where

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

and

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

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

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

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 $\mu = 0$. Fig. 4 shows a histogram and a shifted Rayleigh density function for a cow that belongs to the group of "normal cows".

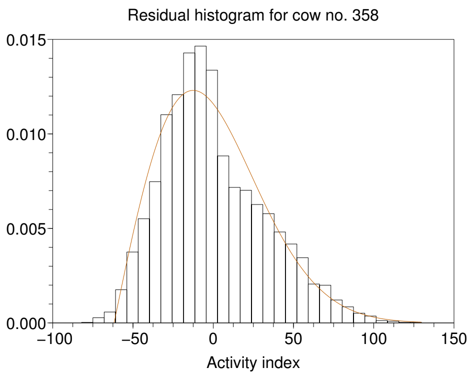

Fig. 4. Residual histogram and an approximated Rayleigh density function for cow no. 358.

The shifted Rayleigh density function has the form

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

for

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

where s is the shape parameter and is found as

$$s = \sqrt{\frac{\sigma^2}{2 - \frac{\pi}{2}}} \quad (15)$$

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

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

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

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

$$\hat{\sigma}^2(k) = \hat{\sigma}^2(k-1) + \frac{1}{T(k)}\left(\varepsilon(k-D_d)^2 - \hat{\sigma}^2(k-1)\right) \quad (17)$$

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

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

$$T(k) = \lambda T(k-1) + 1 \quad (19)$$

where D_d is the estimation delay, l is the time of the actual oestrus detection, l_l 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 $D_h = 72$.

2.2 Likelihood Ratio Test

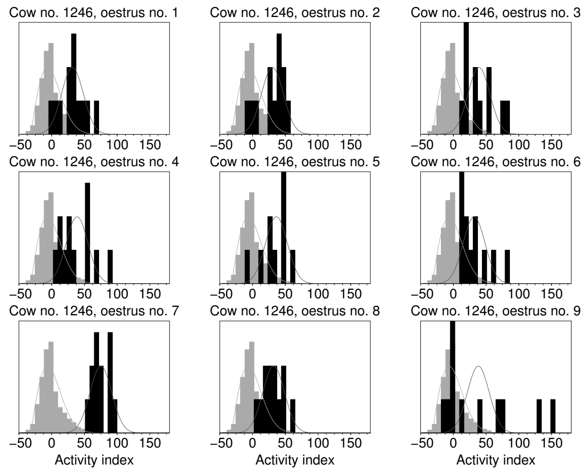

Fig. 5. Histograms of normal and oestrus activity and approximated Rayleigh and gaussian density functions for the 9 oestrus cases for cow no. 1249.

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[h] 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. Fig. 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. Fig. 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

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

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

where the fault occurrence time is restricted to the last M samples. As an oestrus case is not expected to last longer than 24[h] M is determined as $M = 24[h]$. 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 [h] before and after an assumed oestrus case. Mean time to detect ($\hat{\bar{T}}$) is defined as the time delay between an assumed oestrus and the time of detection.

3. 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 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 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

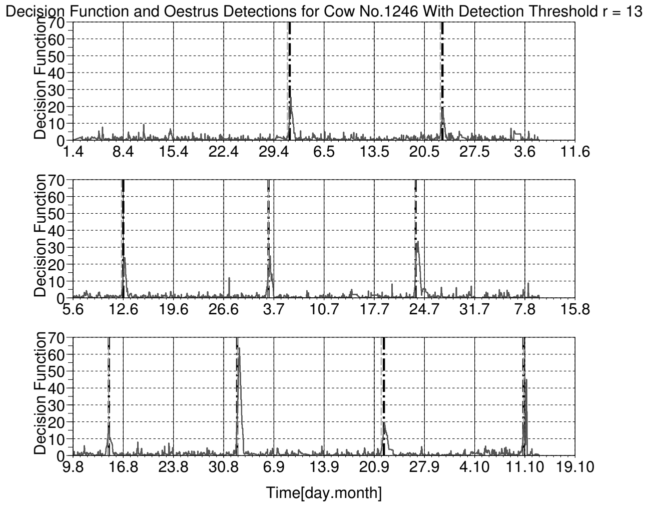

Fig. 6. Decision function for cow no. 1246.

Table 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 4. Detection results

Cow No.	h	Sensitivity	Specificity	Error ratio	$\hat{\bar{T}}$[h]
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

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.

Fig. 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.

A summary of detections results for the entire group of cows studied are shown in Table 3. The detection results for each of the 12 cows are shown in Table 4. Mean time to detect was found as $\hat{\bar{T}} = 2.42$. Comparison of the detection results in Table 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%.

4. 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 diary cows. The detection algorithm was tested on 2323 days of activity, which contained 42 oestrus cases in 12 cows. The results were found to outperform earlier approaches in 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.

5. ACKNOWLEDGMENTS

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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. de 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. 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.

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.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. 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.

D. Schlunsen, H. Roth, H. Schon, 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.