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Improving Oestrus Detection in Dairy Cows by Combining Statistical Detection with Fuzzy Logic Classification

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Abstract: Efficient automated oestrus detection in cows and heifers deeply influences reproductive performance of the animals, and the livestock farmers' profitability. The main problem for practical application of automated detection is the high number generation of false-positive alerts. False alerts could be triggered by changes in feeding or heard behaviour. The detection to false alarm ratio need be very high to get farmers' confidence in an oestrus detection system. Therefore, a method to enhance detection and reduce false alarm probabilities is necessary. Earlier research investigated statistical change detection and hypothesis testing applied on activity sensor data. This paper enhances earlier method by employing fuzzy logic technique to classify oestrus alerts from a model-based detection method utilising the cyclic nature of oestrus. Based on the distribution of the trait period since last detected oestrus, a set of membership functions is introduced with the objective of decreasing the number of false positive alerts as well as improve missed detection rate. The approach was tested on data from twelve diary cows collected over six months. The results show that the number of true detected cases decreased slightly after classification but false positive alerts were almost eliminated.

Keywords: decision support systems, change detection, fault diagnosis, animal husbandry.

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 24 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 labour being expensive in most European countries there is less and less time for focusing on each individual cow. Therefore the request for reliable and economical methods of automatic oestrus detection is rapidly increasing in modern dairy farming. [1]

High detection rates of oestrus with satisfying minimum error rates enhance the reliability of the detection systems. The positive impacts of increased oestrus detection rates were discussed in (Firk et al. (2002)), who emphasised improved insemination results, controlled calving interval and total pregnancy rate. Missed detections of oestrus cases result in missed and untimely inseminations with consequences on farmers' economy: prolonged calving intervals and infertile inseminations (Lehrer et al. (1992)).

In order to improve the detection rate of automatic oestrus, in several investigations oestrus detections have been performed by simultaneous analyses of different traits. The simultaneously combined traits in multivariate analyses were activity, milk yield, milk temperature, milk flow rate, electrical conductivity, concentrate leftovers, dairy cows' behaviour (mounting, genital mucous discharge, genital swelling, frequent urination and restlessness), attempting to mount other cows and time since last oestrus. Most of the authors employed fuzzy logic technique for multivariate oestrus detection, as shown in Table 1. The detection rates for the different combinations ranged between 67% and 90%. In practice however, none of the presented combinations showed any appreciable improvement in error rate (Eradus et al. (1998), Yang (1998), Firk et al. (2003a)).

Fuzzy logic is a well known method applied for control, classification and decision support systems. Fuzzy logic formalises a human-like imprecise reasoning; it represents an ability to reason approximately and judge under uncertain conditions (Zimmermann (2001)).

The main contribution of this paper is to show how fuzzy logic technique can improve the diagnostic performance by regarding the cyclic nature of oestrus. Suggesting that the fuzzy approach could accommodate natural variation in the period of the oestrus cycle, the paper demonstrates

[1] The support of this research by the Danish Research Agency under grant number 2106-05-0046 is gratefully acknowledged.

Table 1. Multivariate oestrus detection using fuzzy logic based testing for dairy cows

Author	Method	Traits	Detection Rate[%]	Error Rate[%]
Eradus et al. (1998)	Fuzzy Inference Systems with 12 Rules Fuzzy Inference Systems with 24 Rules	Activity, Milk Yield, Milk Temperature	79 83	66 48
Yang (1998)	Fuzzy Logic Model	Activity, Milk Yield	90	18
De Mol and Woldt (2001)	Statistical Detection Model+Fuzzy Logic Classifier **(With the Objective of Reducing FP Alerts)**	Activity, Milk Yield, Milk Temperature, Electrical Conductivity, concentrate leftovers,Cow Status	67-71	-
Firk et al. (2003a)	Fuzzy Logic Model	Activity, Milk Yield, Milk Floe Rate, Electrical Conductivity	87-88	28-31
Firk et al. (2003b)	Fuzzy Logic Model **(With the Objective of Reducing FP Alerts)**	Activity, Period Since Last Oestrus	87.9	12.5
Ferreira et al. (2007)	Fuzzy Logic Model	mounting, genital mucous discharge, genital swelling, frequent urination restlessness and time since last oestrus.	84.7	-

how the combination of statistical hypothesis testing and the fuzzy classifier obtain significantly better results than any of the individual methods. The additional classification is obtained without additional sensors or other explicit information. The salient feature about the suggested fuzzy logic model is that it utilises the cyclic nature of oestrus in a very robust way when performing the classification.

As illustrated in Fig. 1, the automated cow status monitoring is realised in two steps. Alerts from a statistical change detection and hypothesis testing algorithm are first generated. Then they are used in a fuzzy logic classifier, where they are evaluated as true or false, using information on prior oestrous detections. Only alerts that are confirmed as true are presented to the herd manager. The paper introduces a set of membership functions, on basis of the distribution of the trait period since last detected oestrus, with the objective of substantially reducing the number of FP alerts as well as keeping the same level of true detected cases of oestrus.

Activity sensor data were available from the Danish Cattle Research Centre in Foulum, Denmark. The data set comprised real-time monitoring of 111 cows over a six months period. Jonsson et al. (2008) scrutinised activity sensor data and suggested algorithms for the detection of oestrus in dairy cows using likelihood ratio tests. The authors discussed properties of different residuals and through identifying probability distribution properties, a dedicated change detection and hypothesis test algorithm was derived. Alerts from tests of the detection algorithm is used by fuzzy logic model to determine whether or not oestrus was to be expected, considering the cyclic nature of oestrus in dairy cows. As the fuzzy logic system acts as a classifier on alerts from the detection model, the number of true positive alerts cannot be increased by this means; combining activity with other traits can improve sensitivity of oestrus detection.

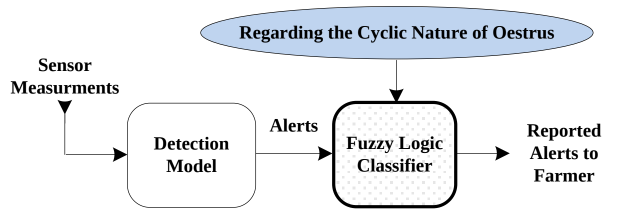

Fig. 1. General scheme for improving oestrus detection

1.1 Fuzzy logic Application with the objective of reducing false positive alerts

In recent years several authors suggested application of fuzzy logic in oestrus detection with the objective of reducing false positive alerts. De Mol and Woldt (2001) used variance of deviations between actual and expected values of sensor readings plus information on reproductive status as input to a fuzzy logic classifier that gave oestrus alerts. The authors came to the conclusion that the number of false-positive alerts was too high for implementation in practice. Combining the trait activity and the period since last oestrus into a fuzzy logic detection model, Firk et al. (2003b) observed a strong reduction in the number of FP warnings and decreased the error rate from 34.6% to 12.5%. The authors obtained this improvement by including information about previous oestrus when this was available. The efficiency of the detection was dependent on the number of cows for which actual information was available on previous oestrus cases.

2. METHOD AND MATERIALS

In this section the derivation of the change detection algorithm and the elimination of periodic oscillations in the activity signal as well as the fuzzy classification are addressed. The elimination of the periodic oscillations is described in 2.1, the derivation of the change detection algorithm is in 2.2 and the fuzzy classification is described in 2.3. The elimination of periodic oscillations and the derivation of the change detection algorithm are described earlier in Jonsson et al. (2008) in a more detailed manner.

2.1 Residual Generator

Cows are animals that rest during the night and are more active during the day. Therefore 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 and described in Jonsson et al. (2008).

Modeling 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. 2 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,

$$y(k) = \mu + A_1\cos(\omega_1 k) + B_1\sin(\omega_1 k) + \dots \qquad (1)$$
$$+A_m\cos(\omega_m k) + B_m\sin(\omega_m k) + \varepsilon(k)$$

where k is the sample instant, ω angular frequency, μ the mean activity and ε a noise component. In vector form,

$$\mathbf{Y} = \mathbf{\Phi}\theta + \varepsilon \qquad (2)$$

where

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

and

$$\theta^T = [\mu\ A_1\ B_1\ \dots\ A_m\ B_m] \qquad (3)$$

The model coefficients are found by using the least squares method. The on-line version of the regression includes a recursive least squares estimator with a forgetting factor. In the recursive version the model coefficients are for each cow found as

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \mathbf{K}(k)\left(y(k) - \mathbf{\Phi}(k)\hat{\theta}(k-1)\right) \qquad (4)$$

where

$$\mathbf{K}(k) = \mathbf{P}(k)\mathbf{\Phi}^T(k) \qquad (5)$$

and

$$\mathbf{P}(k) = \left(\mathbf{P}(k-1) - \frac{\mathbf{P}(k-1)\mathbf{\Phi}^T(k)\mathbf{\Phi}(k)\mathbf{P}(k-1)}{\lambda + \mathbf{\Phi}(k)\mathbf{P}(k-1)\mathbf{\Phi}^T(k)}\right)\frac{1}{\lambda} \qquad (6)$$

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

$$\hat{\varepsilon}(k) = y(k) - \mathbf{\Phi}(k)\hat{\theta}(k) \qquad (7)$$

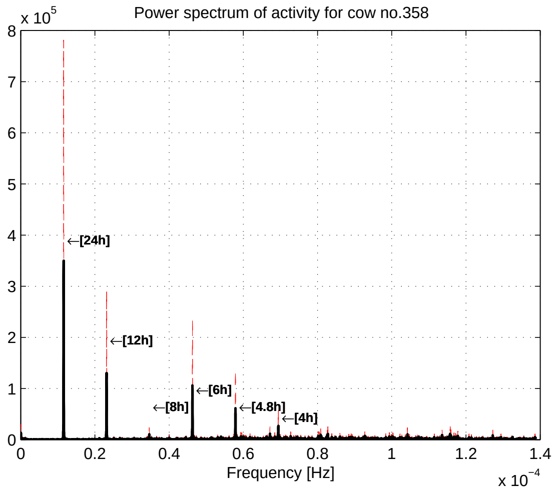

Fig. 2. Power spectrum of activity for cow no. 358.

2.2 Likelihood Ratio Test

Activity data 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. 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. 3 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. 3 it was concluded that a generalised likelihood algorithm (GLR) is a suitable algorithm for the likelihood ratio test. The GLR algorithm has a decision function that maximises 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.

$$g(k) = \max_{1\le j\le k}\ \max_{\mu_1}\ S_j^k(\mu_1) \qquad (8)$$

It was shown in Jonsson et al. (2008) that normal activity is described by a shifted Rayleigh density function and oestrus activity has a gaussian density function. The resulting generalised likelihood ratio test function is,

$$g(k) = \max_{k-M\le j\le k} \sum_{i=j}^{k}\Bigg(\log\left(\frac{2\hat{\sigma}^2(i)}{\sqrt{2\pi\hat{\sigma}^2(i)}(4-\pi)\left(\varepsilon(i)+\frac{\sqrt{\pi\hat{\sigma}^2(i)}}{\sqrt{4-\pi}}\right)}\right)$$
$$-\frac{\left(\varepsilon(i)+\frac{\sum_{q=j}^{k}\frac{\varepsilon(q)}{\hat{\sigma}^2(q)}}{\sum_{q=j}^{k}\frac{1}{\hat{\sigma}^2(q)}}\right)^2}{2\hat{\sigma}^2(i)} + \frac{\left(\varepsilon(i)\sqrt{4-\pi}-\sqrt{\pi\hat{\sigma}^2(i)}\right)}{4\hat{\sigma}^2(i)}\Bigg) \qquad (9)$$

$$g(k) = 0 \qquad for \quad \varepsilon(k) < -\frac{\sqrt{\hat{\sigma}^2(k)\pi}}{\sqrt{4-\pi}} \qquad (10)$$

where $\hat{\sigma}^2$ is the estimated variance and 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

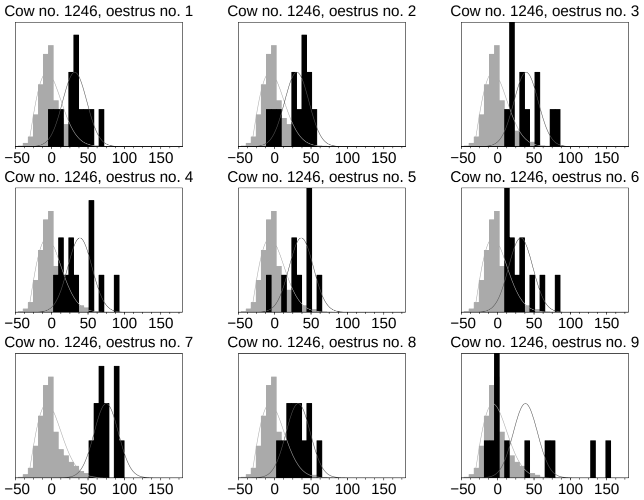

Fig. 3. Histograms of normal and oestrus activity and approximated Rayleigh and gaussian density functions for the 9 oestrus cases for cow no. 1246.

is determined as $M = 24[h]$. A detection is initiated if $g(k) > h$ where h is the detection threshold.

2.3 Fuzzy classification

The implementation of a fuzzy logic classifier should reflect the consideration of the farmer when he is weighing whether an oestrus alert is true or not. The fuzzy logic system comprises three steps:
a) Fuzzification: The test function $g(k)$ is transformed by set-membership functions, illustrated in Fig. 4. Five membership functions 'Short', 'Normal', 'Longish', 'Long' and 'Very Long' were identified from data of the distribution of trait period since last oestrus. The membership 'Normal' contains periods between 20 and 26 days, periods between 30 and 34 days get membership 'Longish'. In case of a missed oestrus period, the expected occurrence of an oestrus case is categorised as 'Long', between 38 and 48 days. The membership to 'Very Long' describes cases of 52 days or higher. Transition between membership functions are linear.

b) Fuzzy Inference: This includes a set of rules. In this paper, rules for the trait period are shown in Table 2. It's obvious that alerts are classified as true if they occur in 'Normal' or 'Long' interval and are classified as false if they occur in 'Short' or 'Longish' or 'Very Long' interval.

c) De-fuzzification: Fuzzy values from fuzzification and fuzzy inference parts are transformed back into values by de-fuzzification. This paper uses a centre-of-area method (Zimmermann (2001)) and the threshold for the de-fuzzified value is 0.5 to raise an alert.

In the present paper, statistical detection is combined with fuzzy classification. It is not possible to classify the first oestrus detection after calving as there is no 'period since Last Alarm'. As a result, the 1st detection is assumed true and 2nd real oestrus case after calving, which would occur in 'Normal' or 'Long' interval after the first true alarm, is the first one that can be correctly classified.

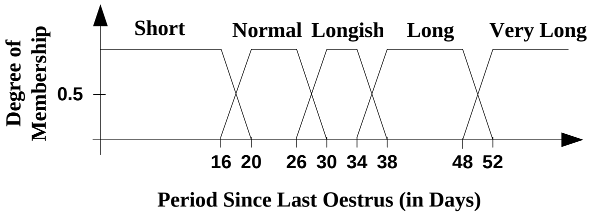

Fig. 4. Membership functions for period since last oestrus Proposed method

Table 2. Rules of fuzzy inference for trait period since Last Detected Oestrus

	Period Since Last Oestrus Alarm		Cow is
If	Normal or Long	Then	In Oestrus
	Short or Longish or Very Long		Not in Oestrus

2.4 Data

The dataset used in this study is the same dataset as used in Jonsson et al. (2008). A more detailed description of the data selection is to be found in Jonsson et al. (2008). 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 Centre over a period of 6 months ("the study period").The activity was measured by means of commercial activity tags placed on the cow's neck.

Data belonging to the 12 cows, that were inseminated, was used for testing the detection algorithm and classification performance.

To validate the performance of the proposed algorithm, visual observations were performed by specially trained personnel at Danish Cattle Research Centre. In Jonsson et al. (2008) additional assumed oestrus cases were chosen where an apparent increasing in activity occurred in the period 18-24 days after a performed insemination if the assumed oestrus case in question was followed by an insemination or a registered observation 18-24 days later. Table 3 shows the number of days of activity data and the number of assumed oestrous cases for each cow in oestrus as well as the total days of activity data and the total number of assumed oestrus cases for the 12 "cows in oestrus".

As an example of the activity data, Fig. 5 shows a plot of the activity data for cow no. 1253 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 oestrus cases are shown as solid vertical lines.

3. RESULTS

The detection performance is determined by probabilities for true and false alerts. De Mol and Woldt (2001) categorised 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 alarm

Table 3. Number of days of activity data and number of assumed oestrus cases for cows which were inseminated

Cow No.	No. of Activity Days	No. of Oestrus Ref.
34	195	1
224	195	2
244	195	3
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

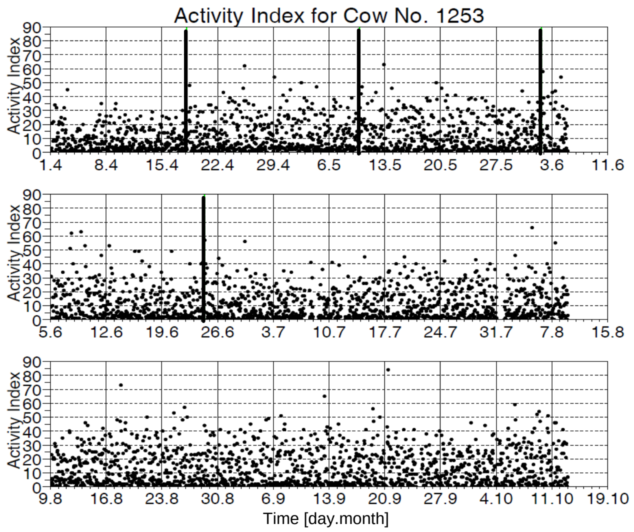

Fig. 5. Activity index (shown as black dots) and assumed oestrus cases (shown as solid vertical lines) for cow no. 1253

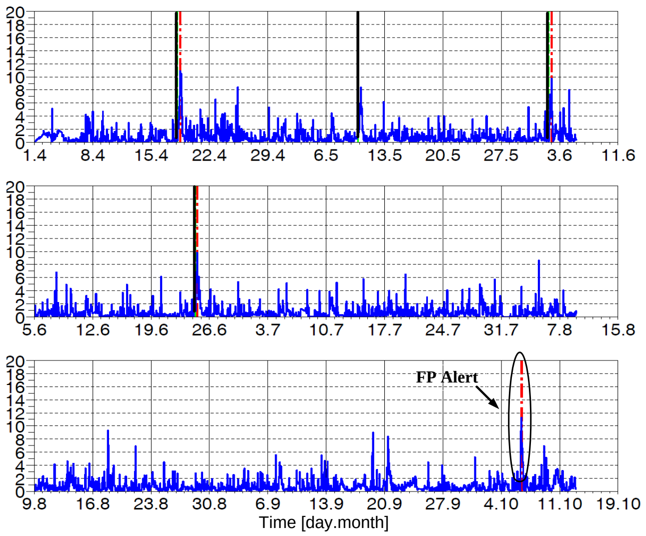

Fig. 6. Decision function for cow no. 1253

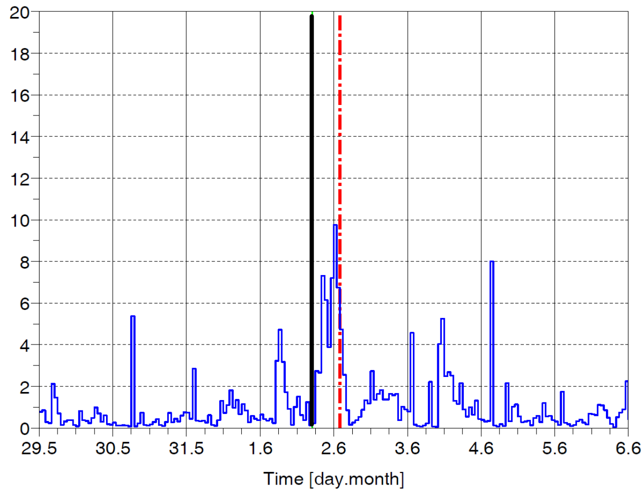

Fig. 7. A zoom-in part of decision function for cow no. 1253

as true negatives (TN). Number of true negatives was in Jonsson et al. (2008) defined as days outside of oestrus without a detection. The statistical detection algorithm, generalised likelihood ratio test (GLRT), was tested in earlier research (Jonsson et al. (2008)) on activity measurements belonging to the 12 cows that were in oestrus during the data period.

As an example, Fig. 6 shows a plot of the decision function from the test performed on data for cow no. 1253. The activity index is shown as blue lines, detections are shown as dash vertical lines and assumed oestrus cases are solid vertical lines in black. When observing Fig. 6 one can see that three actual oestrus cases are detected by statistical detection algorithm while one FP alerts is also generated. According to the date of detections reported in Table 4, the true detection cases are classified using fuzzy logic model as true, because they have occurred in 'Normal' and 'Long' interval. However, the false case was detected 104 days since corresponding last detected oestrus. Hence, after classification using fuzzy logic model, this case is classified as false and is not reported to herd manager. So, in view point of farmer, three detection alerts are seen during the study period that all are true without any false alert. A zoom-in part of decision function for cow no. 1253 is shown in Fig. 7. The activity index is shown as blue lines, detections are shown as dash vertical lines in red and assumed oestrus cases are solid vertical lines in black.

Summary of the detection oestrus method results before and after classification for the entire group of cows studied is shown in Table 5. Sensitivity, specificity and error rate are defined in e.g. Firk et al. (2002) and shown in Table 5. Error rate is referred to as error ratio in this study. The obtained results show that after using fuzzy logic classifier the number of FP alerts decreased significantly while the true detected cases remains at the same level.

4. DISCUSSION

The results presented above show that the proposed method can help establishing better reliance on automated oestrus detection as the number of false alarms is vastly reduced. In this study, the first oestrus detection after

Table 5. Summary of Detection and Classification Results for 12 Cows

	Sensitivity [%] TP/(TP+FN))*100	**Specificity [%] TN/(TN+FP)*100**	**Error Ratio [%] FP/(TP+FP))*100**
Statistical detection alone (Jonsson et al. (2008))	36/(36+6) *100=85.7	2275/(2275+6) *100=99.7	6/(36+6) *100=14.3
Statistical Detector + Fuzzy Classifier (Proposed Method)	35/(35+6) *100=85.3	2275/(2275+1) *100=100.0	1/(35+1) *100=2.8

Table 4. Detection Results for Cow no. 1253

Date of Detect.	**Days Since Last Oestrus**	**Alerts Before Classification**	**Alerts After Classification**
18.4.2006	-	TP	TP
2.6.2006	45	TP	TP
24.6.2006	22	TP	TP
6.10.2006	104	FP	**Removed**

calving is assumed true. The confidence in this first alert can not be as high a alerts classified as true on basis of previous experienced oestrus periods, although in this study, no such false alarms were experienced. The reason is that the GLR test based on observed distributions is already fairly good as a detector.

Considering only the oestrus alerts classified on basis of period since last detection and postponing first insemination till 2nd oestrus after calving would give an even more reliable oestrus alarm system. It could be relevant as and perhaps beneficial for dairy farmers as investigations have been questioning the common practice of inseminating cows as early as possible after calving. Sorensen and Ostergaard (2003) analysed the economic consequences of a postponed first insemination and found that economic effects were highly dependent on the prices of beef. The authors found that in a scenario of 50% decrease in beef prices the herd profit would nevertheless increase by 0.8% by increasing milk production in this way. Arbel et al. (2001) also found that extending the lactations in high yielding cows gave economic advantages. Economic advantages of the extended lactations were found to be even greater for production units under a quota system. As a further potential benefit, Bertilsson et al. (1997) found that the intensity of oestrus increased until oestrus No. 4 and continues at a high level. A herd with a poor reproductive efficiency might shift to a herd with a good reproductive efficiency, if the first insemination was postponed.

5. CONCLUSION

Using activity sensor data, drawing advantage of the cyclic nature of oestrus in dairy cows, a fuzzy logic classifier was used to confirm hypotheses from a statistical change detection algorithm. The combination showed a significant improvement in error rate. Based on the distribution of the period since last detected oestrus, a new set of membership functions was introduced in a fuzzy classifier. The number of false positives was much lower and the number of true positives remained at the same level as judged from analysis of activity data from twelve cows over a six-month period. The results indicate that the combination of the statistical model for the calculation of alerts with the fuzzy logic model for the classification is suitable for reliable oestrus detection in practical usage.

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