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Analysing serial data for mastitis detection by means of local regression

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Abstract

The aim of this study was to assess the potential of detecting mastitis in an automatic milking system using serial information from electrical conductivity of milk. Data from 160 cows from the experimental dairy farm "Karkendamm" of the University of Kiel were available over a period of 14 months. The reference data for incidence of mastitis were treatments (or visual observation of clinical mastitis signs) and the weekly milk somatic cell count (SCC) measurements of all cows. Samples of SCC exceeding 400,000 and 100,000 cells/ml were used as two boundaries together with treatments to define cases of mastitis.

The time series of electrical conductivity of quarter milk were analysed to find significant deviations as a sign for mastitis. Three statistical methods were tested: (1) a moving average, (2) an exponentially weighted moving average and (3) a locally weighted regression. Alerts for mastitis were given when the relative deviation between the measured value and the estimated value exceeded a given threshold value, expressed as a percentage. The three methods provided similar results regarding sensitivity, specificity and error rate. The reliability of alerts varied depending on the threshold value. A low threshold (3%) led to a sensitivity of nearly 100%, however, the specificity was only about 36% and thus the error rate was high (about 70%). Increasing the threshold up to 7% decreased sensitivity to 70% and increased specificity to 84%. In this case, the error rate was slightly reduced to 60%. The three methods showed a good sensitivity and specificity for an appropriate threshold value, but also a high error rate. In the present study, the moving average was the simplest method to detect mastitis and the other methods showed no advantage related to it.

Keywords: Dairy cow; Mastitis; Automatic milking; Serial data; Milk electrical conductivity

1. Introduction

Mastitis can be defined as an inflammation of the mammary gland resulting from the introduction and multiplication of pathogenic micro-organisms in the mammary gland (Heringstad et al., 2000). Mastitis is considered the most costly disease in dairy cattle (Ruegg and Reinemann, 2002). The losses are attributed to reduced milk yield, non-deliverable milk, reduced milk quality, treatment and labour costs, veterinary fees, risk of culling and death (Nielen et al., 1995b). Literature on the economic losses due to clinical or subclinical mastitis strongly differs between studies. The economic impact of clinical mastitis has been estimated to be about 33 to 38% of the total health cost of dairy herds (Fourichon et al., 2001; Kossaibati and Esslemont, 1997). The incidence of mastitis is approximately 30 to 40 cases per 100 cows per

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year (Heringstad et al., 2000; Hillerton and Kliem, 2002). Average economic losses in the U.S. due to mastitis can amount to between \$108 and \$295 (Ott, 1999), but \$200 per cow and year is commonly accepted (Smith and Hogan, 2001). Moreover, the loss of milk production for a clinical case has been calculated to be 375 kg and also the risk of culling following a clinical mastitis increases by a factor of 1.5 to 5 (Seegers et al., 2003).

Product safety and animal welfare in dairy management systems can be improved by means of early detection of diseases such as mastitis (De Mol and Ouweltjes, 2001). This may restrict harmful consequences for the cow and yield losses. Higher demands on the quality of milk also make detection of abnormal milk more important.

Detection of mastitis can be automated by using sensor measurements (Frost et al., 1997). Milk electrical conductivity (EC) was used in computerised systems that have been developed in the last decade in order to detect mastitis (Hamann and Zecconi, 1998; DVG, 2002). EC is determined by the concentration of anions and cations. The most important ions in milk are sodium, potassium and chloride. When mastitis is present, the concentrations of Na^+ and Cl^- in milk increase while concentrations in lactose and K^+ decrease. As a result of this process the value of the EC of milk from the infected quarter increases (Kitchen, 1981).

Relevant and reliable information is essential in order to manage a dairy farm. With conventional milking a lot of this information is obtained visually around and during milking. While the automatic milking systems are equipped with features that collect large amounts of data, they do not supply any information about mastitis. These data have to be transformed into useful information for management support with the aid of appropriate software.

The aim of this research project is to test the use of the EC of milk to detect mastitis in an automated system. Three different univariate procedures were compared based on time series analysis using the electrical conductivity sensor measurements in order to establish a model providing alerts for mastitis. Such a management aid would allow early detection of mastitis at an initial stage with minimum labour requirements, thus optimising not only animal welfare but also the economic decisions of the farmer.

2. Materials and methods

2.1. Data

Data were collected on the experimental farm "Karkendamm" of the Institute of Animal Breeding and Husbandry, Christian-Albrechts-University (Kiel, Germany). Data were recorded from July 2000 till September 2001. During this period 109,739 milkings from 160 cows with 191 lactations were collected. Milking took place in an Automatic Milking System (AMS) with four boxes and an extra cleaning box from Westfalia Landtechnik GmbH, where the number of milkings per day varied and the milking intervals were irregular. A total of 44,074 cow-days were included in the study, at which around 85% originated from cows in first lactation. The mean days in milk was 158. The cows were selected in the AMS on average 2.5 times a day for milking with an average milk yield of 11.3 kg per milking.

In this study, the EC of the milk was used as an indicator for the development of mastitis detection models. The highest value of the EC of the milk was measured in each 200 ml of milk and an average value of the whole milking was recorded. EC ranged between 2 and 9 mS/cm, with an average from 5.3 to 5.5 mS/cm (Table 1).

2.2. Definition of mastitis

Udder health was classified on the basis of the cows' SCC, which was measured weekly from pooled quarter milk samples taken from each cow as well as information on udder treatments. A total of 5,935 SCC tests were carried out with 165,000 cells/ml on average (Table 1). The "Deutsche Veterinärmedizinische Gesellschaft e.V." has stated a value of 100,000 cells/ml as the threshold for mastitis (DVG, 2002). Such a low threshold ensures that most of the mastitis cows are recognised but also supplies a large list of cows classified as infected. The threshold of 100,000 cells/ml was used in the present study, as well as another less strict threshold of 400,000 cells/ml, which represents the European Union maximum bulk milk SCC legal limit for saleable milk. Two

Table 1
Descriptive statistics of the data: number of milkings (n), mean values (x) and standard deviations (s) for the traits electrical conductivity (EC), milk yield, time between milkings and somatic cell count (SCC)

Trait	Unit	n	(x)	s
EC right hind quarter	mS/cm	106,841	5.44	0.58
EC left hind quarter	mS/cm	108,260	5.34	0.53
EC right front quarter	mS/cm	105,856	5.26	0.53
EC left front quarter	mS/cm	106,004	5.35	0.56
Milk yield per milking	kg	105,510	11.31	3.77
Time between milkings	h	109,548	9.41	2.77
SCC	(1000/ml)	5935	163	371

variants of mastitis definition were used in this investigation:

1) Treat+100: treatment performed or a SCC>100,000 cells/ml,
2) Treat+400: treatment performed or a SCC>400,000 cells/ml.

The milking days were classified as "days of health" or "days of mastitis". If two succeeding SCC measurements either both exceeded the threshold or both did not, all days between these measurements were also defined as "days of mastitis" or "days of health", respectively. In the other case, the day on which the SCC was recorded, and 2 days after and 2 days before were defined according to this SCC-value and the days in the middle were set to uncertain days (an example is given in Fig. 1).

In addition, the day on which a treatment took place plus 2 days before and 2 days after were set to "days of mastitis", and up to 10 days after the last treatment were considered "uncertain days". A mastitis block was defined as an uninterrupted sequence of "days of mastitis".

With these definitions, depending on the SCC threshold, 236 and 571 mastitis blocks were found with a mean mastitis length of 16.6 and 24.5 days for 400,000 and 100,000 cells/ml, respectively. Depending on the definition of mastitis, an average of 7 and 24 cows, respectively, suffered from mastitis per day.

2.3. Univariate methods

Three different univariate time series methods for the trait EC were compared. These procedures are based on the expected estimation values from the last available data and then are compared with the true values. If the measured value of EC deviated from the predicted value amounting to at least the threshold value, the system supplied an alarm signal.

2.3.1. Moving average

In some management information systems "Moving-Average Models" (MA) are already used to monitor udder health.

$$Y'_t = \frac{1}{N}\sum_{k=1}^{N} Y_{t-k} \quad N = 10$$

With this procedure a new estimate of the value of EC (Y'_t) at each milking is calculated from the mean of the last recordings N, so that each milk EC recording has the same weight in the forecasted mean. The smoothing effect of the moving average increases with the increasing number of considered observations in history. The analysis for the trait was performed with $N=10$ observations, which was chosen in agreement with common management practice (Van Bebber et al., 1999).

2.3.2. Exponentially weighted moving average

With the "Exponentially Weighted Moving Average" (EWMA) the expected value is calculated by taking all the preceding milk recordings into account. The weights decline exponentially depending on the smoothing parameter (α) with increasing time distance between historical and actual value.

$$Y'_t = \alpha \cdot Y_{t-1} + (1-\alpha) \cdot Y'_{t-1}$$

Through variation of a factor (α) the weighting can be changed. The higher the value of α, the more strongly weighted are the last values. Small values of α mean a strong smoothness. In a preliminary investigation, different weights were tested (α=0.2, 0.4, 0.6, 0.8) to find the most suitable parameter. The best results were found for an α-value of 0.2, which was used in this study.

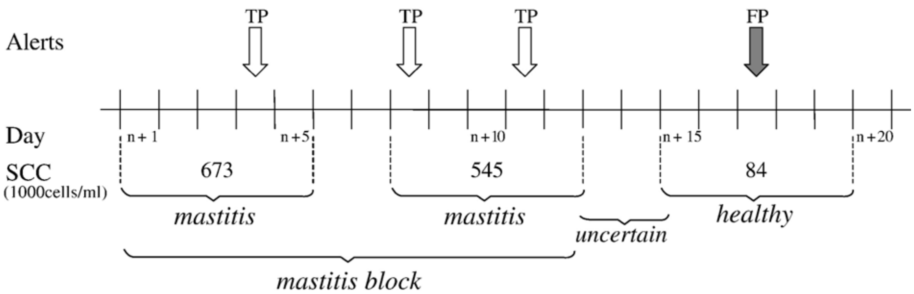

Fig. 1. Example of definition of health status taking into account the somatic cell count (SCC) and the classification of the alerts with three true positive (TP) alarms in the mastitis block and one false positive (FP) alert outside the mastitis period.

2.3.3. LOESS

The third approach is the LOESS method, a procedure in SAS/STAT (SAS, 2005), more descriptively known as locally weighted polynomial regression. A non-parametric method for estimating regression surfaces or curves is performed. One advantage of this method is that a global function of any form which fits a model to the data is not necessary. Instead, only segments of the data are fit, which allows great flexibility.

At each point in the data set a first-degree polynomial was fit to a subset of the data within a chosen neighbourhood of the point whose response (EC) was being estimated. The fraction of data which is used for the regression in each local neighbourhood is called the "smoothing parameter", which determines the smoothness of the estimated curves. The smaller the smoothing parameter is, the closer the line fits the chosen data points. There are several ways to determine the smoothing parameter. In this study, it was estimated after each new observation by iteratively testing different values of the smoothing parameter ranging from 0.1 to 1 at 0.01 intervals. The value should minimise a bias-corrected Akaike information criterion. This criterion incorporates both the tightness of the fit (the distances from the data points to the curves) and model complexity (Cohen, 1999). The smoothing parameter was mostly in the range from 0.25 to 0.6.

In the LOESS method, the individual time distances of the observations are additionally taken into account. More weight is given to points in time close to the point whose response is being predicted and less weight to points farther away.

$$w(y) = \begin{cases} (1-|x|^3)^3 & \text{for } |x|<1 \\ 0 & \text{for } |x|\geq 1 \end{cases}$$

The weight for a specific point in any localised subset of data is obtained by evaluating the presented weight function ($w(y)$) at the distance between that point and the estimated point, after scaling the distance (x) so that the maximum absolute distance over all points in the subset of data is one.

This procedure was modified to monitor EC, because only previous observations were used to forecast the actual value. The data value of the current milking was compared to the historical data, as was used to investigate critical changes in the automobile market in the United States (Powers et al., 2003). The estimation of the smoothing parameter is carried out after each new milking, this means a new size of the subsets for fitting the lines using the new information. When the EC shows a considerable increase compared to the predicted value, the monitoring system is supposed to detect this change and to supply an alert.

An example of how the procedure works is given in Fig. 2. In this example, 7 observations are used to fit the line. The scaling distance (X) used for the weight function above is obtained by $X_{t-n}=i_{t-n}/i_{\max}$, where i is the distance from each point to the point of estimation. The

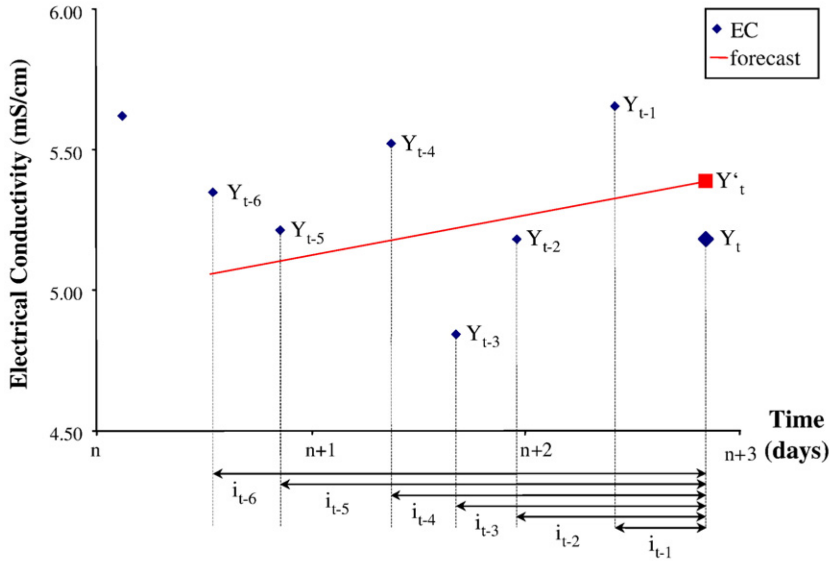

Fig. 2. Example of LOESS where the smoothing parameter determines that 7 points are used to fit the line. The scaling distance used for the weight function is $X_{t-n}=(i_{t-n}/i_{t-6})$. The line is then fitted for all points in the subset by means of weighted least square.

line is fitted to these observations by means of weighted least squares.

2.4. Test procedure

The system provided an alert signal when the relative deviation between the actual observation and the estimated value exceeded a given percentage threshold (Firk et al., 2003). The model performance was assessed by comparing these alerts with the actual occurrences of mastitis.

The concerning day of observation was classified as true positive (TP) if the threshold was exceeded on a day of mastitis, while a non-detected day of mastitis was classified as false negative (FN). Each milking day in a healthy period was considered a true negative case (TN) if no alerts were generated and a false positive case (FP) if an alert was given. An example for the classification of the alarms is shown in Fig. 1.

The accuracy of these procedures was evaluated by the parameters sensitivity, block sensitivity, specificity and error rate.

The sensitivity represents the number of correctly detected days of mastitis of all days of mastitis:

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP}+\text{FN}} \times 100$$

While sensitivity considers each single day of mastitis, for the block sensitivity each mastitis block was considered as a TP case if one or more alerts were given in the first 5 days of this mastitis block, and a FN case otherwise.

The specificity indicates the percentage of correctly found healthy days from all the days of health:

$$\text{specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}} \times 100$$

The error rate represents the percentage of days outside the mastitis periods, from all the days where an alarm was produced:

$$\text{error rate} = \frac{\text{FP}}{\text{FP}+\text{TP}} \times 100$$

In addition, the number of FP and TP cows per day is given. TP and FP cows/day are the average number of cows per day which were rightly and wrongly declared as diseased, respectively.

3. Results and discussion

For the detection of mastitis, it was less important that all days in a mastitis block were recognised, but it was decisive that a case of mastitis was detected early. The detection had to take place within the first 5 days of the mastitis block. Therefore the block-sensitivity is considerably more important than sensitivity.

The results obtained for the three procedures for the different test parameters depending on the mastitis definition are shown in Figs. 3 and 4. The three methods differed only slightly from each other with regard to the parameters verifying the model. Block sensitivity decreased with increasing threshold value. The best results for block-sensitivity for the variant Treat+100 were obtained by MA and EWMA, where the decrease in sensitivity depending on the threshold value was smaller (from 99.8 to 58.0%) compared to the decrease in LOESS (from 99.6 to 40.5%). The same tendency was observed for the variant Treat+400. Nevertheless, the sensitivities were at a higher level due to more evident cases being considered to show higher changes in EC.

On the contrary, specificity increased with increasing threshold value, as expected. Lower specificities were obtained by MA and EWMA (with 25.7 to 88.1% for the variant Treat+100). The best results were reached by LOESS with specificities between 36.5 to 93.7% for the variant Treat+100. The specificities obtained for the other variant (Treat+400) were similar.

The error rate decreased moderately with increasing threshold value, from 66.3 to 43.9% for the three methods with variant Treat+100. For the variant Treat+400 no differences were observed between the three methods either, but the error rates were at a higher level compared to the first variant. The reason for the higher error rates is the great number of "days of health" compared to "days of mastitis" for the second variant, so that the likelihood of the appearance of false positive alerts in comparison with the true positive alerts is very high.

The number of FP cows/day had a stronger decrease with higher threshold than the number of the TP cows/day using any of the methods (Figs. 5 and 6). Slightly higher numbers of TP cows/day were calculated by MA and EWMA (varying from 22.1 to 7.6 for the variant Treat+100) in comparison to LOESS (varying from 19.6 to 4.7 for the variant Treat+100). The number of FP cows/day was slightly higher for MA and EWMA (varying from 43.3 to 6.9 for the variant Treat+100) than for LOESS (it varying from 37.1 to 3.7 for the variant Treat+100). For the variant Treat+400 the trend was the same, however, the number of the TP cows/day was smaller and the number of the FP cows/day was larger compared to the variant Treat+100.

In general, the sensitivity and the specificity are inversely correlated: the higher the sensitivity, the lower the specificity. If one wanted to use the tests to determine the presence of mastitis, one would adopt a cut-off (threshold) value. The threshold value, therefore,

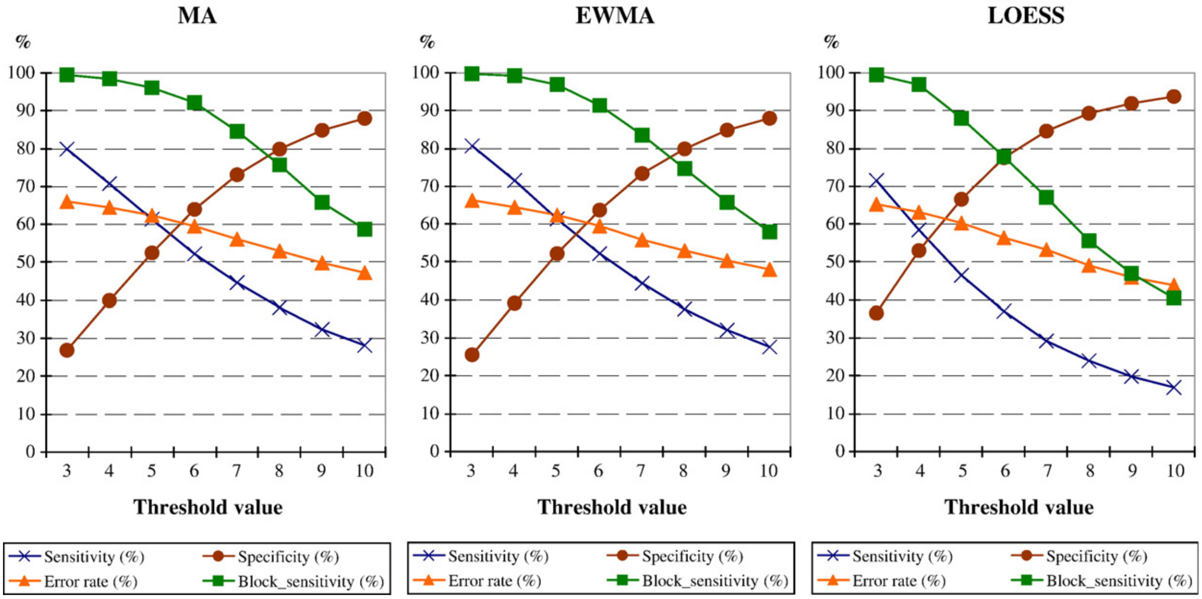

Fig. 3. Comparison between the three investigated analysing procedures (MA: Moving Average, EWMA: Exponentially Weighted Moving Average and LOESS) for the variant with mastitis definition Treat+100.

determines the sensitivity and specificity. The value actually chosen as cut-off would depend on the purpose of the test.

One way to obtain more insight in an optimal cut-off value is to calculate the sensitivity and specificity at several cut-off values. Next, the results are plotted in a so-called ROC curve (Figs. 7 and 8). In such a plot, the false positive fraction (1-specificity) is at the *X*-axis and the true positive fraction on the *Y*-axis, and shows how the two quantities vary together as the decision is varied (Noordhuizen et al., 1997). The higher the curve, the greater the accuracy. The ROC curves (Figs. 7 and 8) illustrate once again that all three procedures supply similar accuracy.

In the preferred diagnostic procedure, adjustments of the decision threshold are made to produce the best ratio

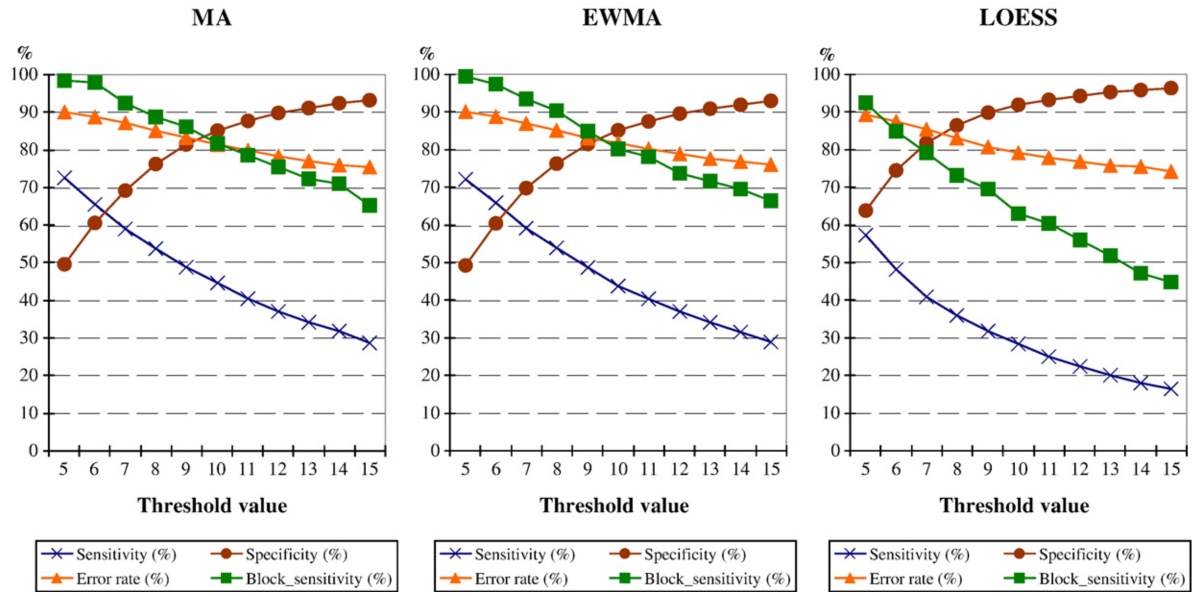

Fig. 4. Comparison between the three investigated analysing procedures (MA: Moving Average, EWMA: Exponentially Weighted Moving Average and LOESS) for the variant with mastitis definition Treat+400.

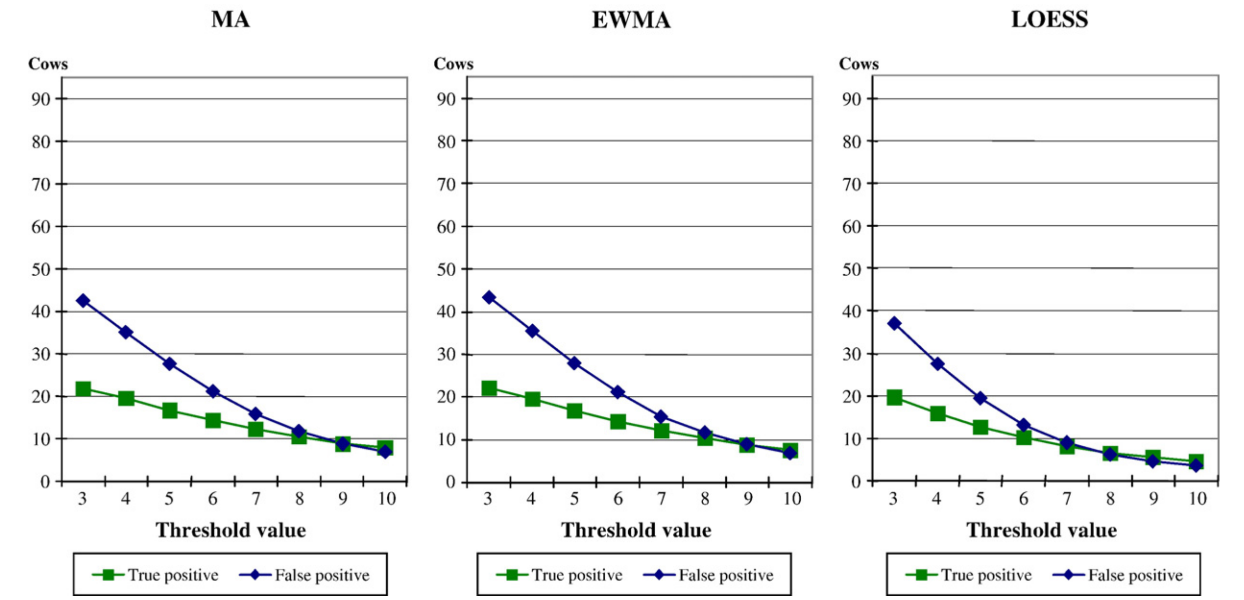

Fig. 5. Comparison of the values of true positive and false positive cows/day between the three investigated analysing procedures (MA: Moving Average, EWMA: Exponentially Weighted Moving Average and LOESS) for the variant with mastitis definition Treat+100.

of positive to negative decisions and ultimately to produce the best balance among the four possible decision outcomes for the situation at hand, and hence to maximise the utility of the set of decisions made over time (Swets et al., 2000). In such a curve, tests that plot in the left upper corner are best (high block-sensitivity and high specificity). The optimal threshold value can then be chosen depending on the use of the test to determine whether a high sensitivity or a high specificity is wanted.

The aim of the study is to develop a test model with sufficient accuracy. The gold standard of human observation to detect clinical mastitis depends on the skill of the milker and the severity of the case, but an average sensitivity of 80% has been reported (Hillerton and

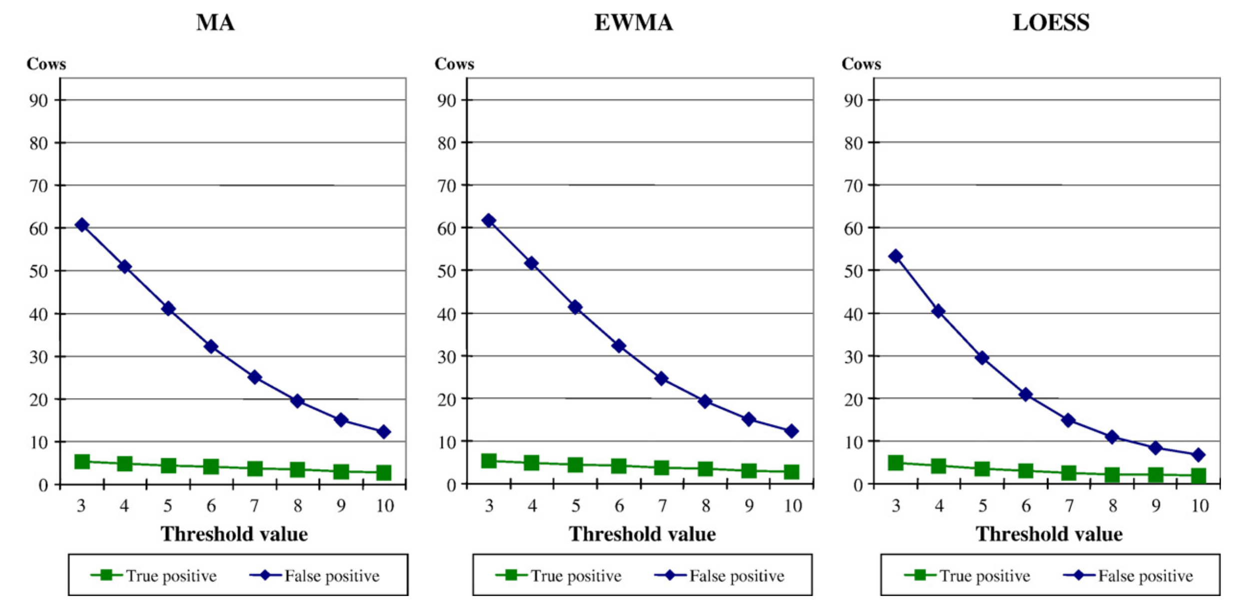

Fig. 6. Comparison of the values of true positive and false positive cows/day between the three investigated analysing procedures (MA: Moving Average, EWMA: Exponentially Weighted Moving Average and LOESS) for the variant with mastitis definition Treat+400.

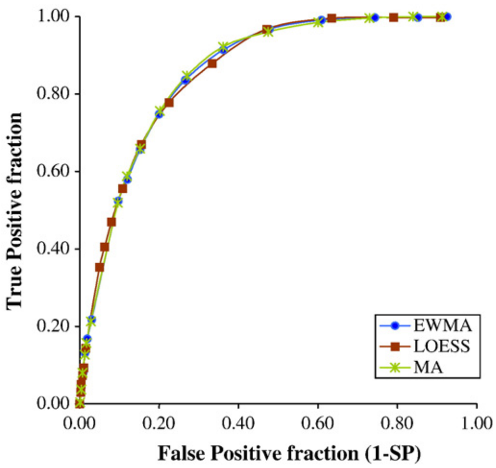

Fig. 7. ROC curve of the three investigated analysing procedures (MA: Moving Average, EWMA: Exponentially Weighted Moving Average and LOESS) for the variant with mastitis definition Treat+100.

Kliem, 2002). Therefore, a value of at least 80% for the block-sensitivity is desired.

With these two concepts, the threshold values were set for the different methods and for the two definitions of mastitis (Table 2).

According to Hamann and Zecconi (1998) using EC in milk as a mastitis indicator provides very variable results for sensitivity and specificity. In a meta-analysis of the published information, the authors summarised an average sensitivity and specificity of 68 and 82% for detection of mastitis based on EC (different mastitis definitions were used). Nielen et al. (1995a,b) found a sensitivity of 75% and 55% for clinical and subclinical mastitis, respectively, and a specificity of 90% (quarters without presence of bacteria and SCC <200,000 cells/ml were used as a negative control). De Mol et al. (1997) indicated a sensitivity of 37 to 50% and of 24 to 76% for clinical and subclinical mastitis, respectively, and a high specificity between 99.4 and 96% in case of a time-series model for the EC of milk and an SCC threshold of 500,000 cells/ml.

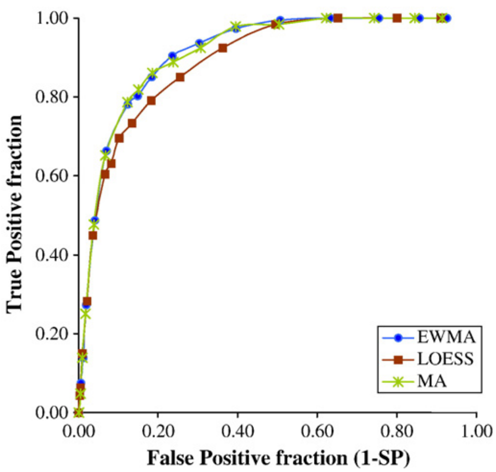

Fig. 8. ROC curve of the three investigated analysing procedures (MA: Moving Average, EWMA: Exponentially Weighted Moving Average and LOESS) for the variant with mastitis definition Treat+400.

Van Asseldonk et al. (1998) found by consultation with experts that an implementation of the EC of quarter milk would result in a sensitivity of 54% and 51% and a specificity of 79% and 80% for clinical and subclinical mastitis detection, respectively.

Moreover, Mele et al. (2001) obtained a sensitivity between 65 to 83% for clinical mastitis and 84% for subclinical mastitis (the SCC threshold was 300,000 cells/ml), and a high specificity, 97%. In a recent study, Norberg et al. (2004) estimated a sensitivity of 80 and 45% for clinical and subclinical mastitis and a specificity of 74.8%; in this study the udder health was based on veterinary treatments and bacteriological samples. Different results between the studies may mainly be caused by distinctions in the definition of mastitis and the measurement technique. In the present study mastitis was defined on the basis of treatments and on an SCC threshold of 100,000 and 400,000 cells/ml; other authors have defined mastitis using different SCC thresholds. The estimation of classification parameters depends on data basis. There is a high variance of mastitis prevalence in different herds. Furthermore, in this study, the specificity for mastitis was calculated regarding all cows. This has not been the case in other studies where only cows without any mastitis case during the test period have been used.

A reason for the large error rate in this study was probably the measurement of the EC. The EC of milk depends on its point of measurement. The EC of foremilk, before alveolar milk ejection occurs, gives better information on the health status than other milk

Table 2
Results for the three models for the best threshold value

Treat+ 100	Threshold	Block-sensitivity	Specificity	Error rate	TP cows/day	FP cows/day
MA	7%	84.7	73.0	56.2	12.3	15.7
EWMA	7%	83.6	73.4	56.0	12.2	15.5
LOESS	5%	87.9	66.6	60.4	12.8	19.5
Treat+ 400	Threshold	Block-sensitivity	Specificity	Error rate	TP cows/day	FP cows/day
MA	9%	86.1	81.4	83.3	3	15.1
EWMA	9%	85.0	81.6	83.2	3	15.0
LOESS	6%	85.0	74.5	87.4	3	20.8

fraction (Woolford et al., 1998; Barth et al., 2000). Unfortunately, in the present study, the EC was averaged across the whole quarter main milk, and no measurement of foremilk was available. The slight difference between the three studied methods might have been caused by the inaccuracy of the information trait.

4. Conclusion

Milk entering the bulk tank must be from cows that are not visibly ill, indicating that a general health check has to be performed before the milk is stored. The development of high-performance mastitis detection programs for effective controlling is important in connection with automatic milking systems, where there is no detection by visual observation in the milking barn during milking.

The three univariate methods used to detect mastitis based on EC showed similar results. A decrease in sensitivity with increasing threshold leads to a decrease in specificity. The univariate analysis of the EC trait by the three methods was satisfying for sensitivity and specificity. However, the corresponding error rates were too high. This might be explained by an insufficient relationship of the electrical conductivity trait measured from the AMS with the definition of mastitis in this study.

There are several approaches to reduce the FP alerts. First, further research to develop and test multivariate models is needed, in which other additional variables and meta-information are taken into account. Second, more explanatory traits could provide some useful information in terms of mastitis detection as well as detection of other abnormalities in the cow. Third, an improvement in the sensor technique could lead to more reliable estimations and a better detection of mastitis.

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