AUTOMATED MASTITIS DETECTION IN DAIRY COWS USING DIFFERENT STATISTICAL METHODS

Dissertation
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General Introduction

The situation in dairy farms has changed considerably over the last few years. The number of dairy farms has been continuously decreasing, whereas milk production per cow has noticeable been increasing, partly due to an intensively genetic selection (ADR, 2005). However, this increase in productivity entails some negative effects as well, namely higher incidences of diseases and infertility. Cows with a high milk yield have a higher risk of mastitis than cows with a lower milk yield (Oltenacu and Ekesbo, 1994; Hinrichs et al., 2005).

Mastitis is considered the most costly disease in dairy cattle and remains as one of the major problems concerning the dairy industry (Heringstad et al., 2000). Average economic losses due to mastitis are estimated to be around 150 Euro per cow and year (DVG, 2002). Moreover, udder disease is the second reason for leaving the herd, which is the cause for 14.6% of cows leaving their herds in Germany (ADR, 2005). The average age when leaving the herd is 5.4 years, which means that the average is only approximately 2.5 years (ADR, 2005), and this has a large impact on the costs. Beside economical costs, another issue has increased in importance, namely, the awareness of consumer and dairy organisations in regard to animal welfare, and mastitis is unquestionably a factor that reduces it (Buxadé, 2006; Schukken et al., 2003).

Mastitis is an inflammation of the mammary gland resulting from the introduction and multiplication of pathogenic micro-organisms into the mammary gland (Wendt et al., 1994). Mastitis can be classified as clinical and subclinical mastitis, depending on the response to the infection (DVG, 2002). Clinical mastitis is associated with a visual detectable symptom, such as an inflamed udder or changes in the appearance of the milk. However, subclinical mastitis shows no visible external changes to indicate its presence, making its diagnosis more problematic since it is only detected in laboratory examinations (DVG, 2002). Subclinical mastitis leads not only to a loss in yield, but also to financial penalties for high cell counts in the bulk tank milk exceeding 400,000 cells/ml of milk (Milchverordnung 2004).

With the introduction of the Automatic Milking System (AMS), the identification of udder infections can no longer be based on visual observation. On the contrary, control programs based on sensor measurements managing the health status of the cows have to be introduced.
It should be noted that the herd size has continuously increased in the last decades (ADR, 2005). Also in large herds, where visual observation and monitoring of all cows needs a lot of time, these control programs are desired.

Somatic cell counts measure the inflammatory response to an intramammary infection, and are widely used in the dairy industry (Schukken et al., 2003). Cell counts provide useful information, but they have limitations. In milk-recorded herds, samples from each cow are taken regularly and the somatic cell count is calculated. However, the results are available after a few days and from the test day only, making the usefulness of this examination less appropriate for mastitis detection.

Timely detection of mastitis is very important, not only to reduce the economic impact due the production losses, but also to minimise the negative effects on animal welfare. The mastitis detection model should enable the farmer to identify diseased cows early so as to protect the cows and also to reduce the use of medicines, the incidence and the severity of mastitis. Milk quality and consumer health are thus guaranteed. Monitoring tools are required to find the areas of risk within the herd. It is inevitable that more thorough udder health programs and monitoring systems be developed and implemented (Schukken et al., 2003).

The aim of the present study was to detect and quantify variations in the serial information (milk yield, electrical conductivity, milk flow, milk frequency, etc.), to analyse the interrelationship between the different variables and mastitis, and to finally develop a mastitis detection model by the application of different methods which use the serial data recorded in a management information system. This model could support farmers in optimising decisions concerning the monitoring of mastitis. In this way, management decisions would be efficiently supported in order to optimise both animal welfare and economical decisions.

Mastitic milk has a higher electrical conductivity than normal milk. This is due to tissue damage and the subsequent increase in sodium and chloride ions in milk (Hamann and Zecconi, 1998). Conductivity sensors are being incorporated into many new automated milking systems. The change in electrical conductivity is one of the earliest manifestations associated with new infections making the early detection and recording of possible mastitis cases routine. The aim of the first chapter was to test the use of electrical conductivity of milk (EC) in an automated system to detect mastitis. Three different univariate procedures based
on time-series analysis were compared using electrical conductivity sensor measurements in order to establish a model to provide alerts for mastitis.

Management information systems supply a large amount of sensor measurements, which have limited application on their own. However, this data, supported by robust models which integrate the measurements from several sources, can be used to monitor the health of cows’ udders. In the recent years, powerful computer techniques have been used to address herd management challenges. One of these techniques is artificial intelligence. These methods have been used successfully for oestrus detection instead of classical statistical methods (Firk et al., 2003, Krieter et al., submitted). In chapters two and three, multivariate analyses were performed. In the second chapter, a Fuzzy Logic model was developed using the traits EC, milk yield and milk flow rate.

In the third chapter, another technique from the expert systems was used. The technique of Neural Networks was developed in the field of artificial intelligence to emulate a biological neural net in the human brain as an information processing system. In this chapter, a Neural Network model was developed using additional information from the lactation stage.

References


Chapter One:

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 the milk. Data from 160 cows of the experimental dairy herd “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 reported 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 and the other methods showed no advantage related to moving average to detect mastitis.

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, 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 et al. 1997). The incidence of mastitis is approximately 30 to 40 cases per 100 cases per year (Heringstad et al. 2000; Hillerton and Kliem, 2002). Average economic losses in the U.S. due to mastitis can cost between $108 and $295 (Ott, 1999), but $200 per cow and year is commonly acceptable (Smith and Hogan, 2001). Moreover, the loss of milk production for a clinical case has been calculated to be 375 kg and also an increasing risk of culling following a clinical mastitis 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). Early detection of diseases such as mastitis 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 were 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 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. This data has to be transformed with the aid of appropriate software into useful information for management support. The aim of this research project is to test the use of EC of milk in an automated system to detect mastitis. Three different univariate procedures based on time series analysis using the electrical conductivity sensor measurements in order to establish a model providing alerts for
mastitis were compared. Such a management aid would allow early detection of mastitis at an initial stage with minimum labour requirements, so that, not only animal welfare but also economic decisions of the farmer would be optimised.

2. Material and methods

2.1. Data

The data was collected on the experimental farm “Karkendamm” of the Institute of Animal Breeding and Husbandry, Christian-Albrechts-University (Kiel, Germany). Data was 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 4 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, whereby 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 of 5.3 to 5.5 mS/cm (Table 1).

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

<table>
<thead>
<tr>
<th>Trait</th>
<th>Unit</th>
<th>n</th>
<th>mean</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>EC right hind quarter</td>
<td>mS/cm</td>
<td>106,841</td>
<td>5.44</td>
<td>0.58</td>
</tr>
<tr>
<td>EC left hind quarter</td>
<td>mS/cm</td>
<td>108,260</td>
<td>5.34</td>
<td>0.53</td>
</tr>
<tr>
<td>EC right front quarter</td>
<td>mS/cm</td>
<td>105,856</td>
<td>5.26</td>
<td>0.53</td>
</tr>
<tr>
<td>EC left front quarter</td>
<td>mS/cm</td>
<td>106,004</td>
<td>5.35</td>
<td>0.56</td>
</tr>
<tr>
<td>Milk yield per milking</td>
<td>kg</td>
<td>105,510</td>
<td>11.31</td>
<td>3.77</td>
</tr>
<tr>
<td>Time between milkings</td>
<td>h</td>
<td>109,739</td>
<td>9.41</td>
<td>2.77</td>
</tr>
<tr>
<td>SCC (1,000/ml)</td>
<td></td>
<td>5,935</td>
<td>165</td>
<td>402</td>
</tr>
</tbody>
</table>
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 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 where the SCC was recorded, and two days after and two 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 Figure 1).

![Figure 1](image)

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.
In addition, the day where a treatment took place plus two days before and two days after were set to “days of mastitis” and up to ten 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 on average 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 they 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.

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 \( Y'_t \) on 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).

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 (\( \alpha \)) with increasing time distance between historical and actual value.
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 great smoothness. In a preliminary investigation different weights were tested (α = 0.2, 0.4, 0.6, 0.8) to find the most suitable parameter, and the best results were found for an α-value of 0.2, which was used in this study.

**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 minimize 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). Most of the times lay the smoothing parameter in the range 0.25 to 0.6.

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

\[
Y'_i = \alpha \cdot Y_{i-1} + (1-\alpha) \cdot Y'_{i-1}; \quad \alpha = 0.2
\]

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 the 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 against the historical data, as it 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, which 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 supply an alert.

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

---

**Figure 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 $X_{t-n} = \frac{i_{t-n}}{i_{t-6}}$. The line is then fitted for all points in the subset by means of weighted least square.
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 Figure 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:

\[
sensitivity = \frac{TP}{TP + FN} \times 100
\]

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 five 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:

\[
specificity = \frac{TN}{TN + FP} \times 100
\]

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

\[
error\ rate = \frac{FP}{FP + TP} \times 100
\]

In addition, the number of FP and TP cows per day is given. The number of FP cows per day is quite an important information. TP and FP cows/day mean the average number of cows per day which were rightly and wrongly declared as diseased and thus stand for the effort of the farmer with respect to mastitis monitoring.
3. Results and discussion

For the detection of mastitis, it was not so important that all the days in a mastitis block were recognised, but it was decisive that a mastitis case was detected early. It was determined that 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 Figures 3 and 4. Regarding the parameters verifying the model, the three methods differed only slightly from each other. Block sensitivity decreased with increasing threshold value. The best results for block sensitivity for the variant Treat+100 were reached 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.

Figure 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.
As expected, specificity on the contrary increased with increasing threshold value. 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 could be observed between the three methods as well, but the error rate 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 with “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.

![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.](image)

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 (Figure 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 with LOESS (varying from 19.6 to 4.7 for the variant Treat+100).
Figure 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.

Figure 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.
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 were 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 sensitivity, the lower specificity. If one wants to use the tests to determine the presence of mastitis, one would to adopt a cut-off (threshold) value. The threshold value, therefore, determines the sensitivity and specificity. The value actually chosen as cut-off, will depend on the purpose of the test. In case of a very contagious disease, one would aim for a high sensitivity to prevent or minimize the risk of assigning a truly diseased animal as negative. If the measure to be adopt is slaughter of affected animals, the specificity also would be important.

Figure 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.
One way to get 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 (Figure 7 and Figure 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. The higher the curve, the greater the accuracy. The ROC curves (Figures 7 and 8) illustrate once again that all three procedures supply similar accuracy.

![ROC Curve](image)

Figure 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.

In the preferred diagnostic procedure, adjustments of the decision threshold are made to produce the best ratio 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. In such a curve, tests that plot in
The optimal threshold value can then be chosen depending on the use of the test 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, 2000). Therefore, a value of at least 80% for the block-sensitivity is desired.

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

Table 2

<table>
<thead>
<tr>
<th>Treat+100</th>
<th>Threshold</th>
<th>Block-Sensitivity</th>
<th>Specificity</th>
<th>Error rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA</td>
<td>7%</td>
<td>84.7</td>
<td>73.0</td>
<td>56.2</td>
</tr>
<tr>
<td>EWMA</td>
<td>7%</td>
<td>83.6</td>
<td>73.4</td>
<td>56.0</td>
</tr>
<tr>
<td>LOESS</td>
<td>5%</td>
<td>87.9</td>
<td>66.6</td>
<td>60.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Treat+400</th>
<th>Threshold</th>
<th>Block-Sensitivity</th>
<th>Specificity</th>
<th>Error rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA</td>
<td>9%</td>
<td>86.1</td>
<td>81.4</td>
<td>83.3</td>
</tr>
<tr>
<td>EWMA</td>
<td>9%</td>
<td>85.0</td>
<td>81.6</td>
<td>83.2</td>
</tr>
<tr>
<td>LOESS</td>
<td>6%</td>
<td>85.0</td>
<td>74.5</td>
<td>87.4</td>
</tr>
</tbody>
</table>

According to Hamann and Zecconi (1998) using EC in milk as a mastitis indicator leaded to very variable results for sensitivity and specificity. The authors summarised in a meta-analysis of the published information 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, 1995b) found a sensitivity of 75% and 55% for clinical and subclinical mastitis, respectively, and a specificity of 90% (quarters without bacteria presence and SCC < 200,000 cells/ml were used as 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 EC of milk and a SCC threshold of 500,000 cells/ml.
Van Asseldonk et al. (1998) found by consultation of experts that an implementation of 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 be caused mainly by distinctions in the definition of mastitis and in the measurement technique. In the present study mastitis was defined on the basis of treatments and on a 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 the different herds. Furthermore, in this study, the specificity for mastitis was calculated regarding all cows, which was not the case in other studies where only cows without any mastitis case during the test period were used.

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

4. Conclusion

Milk that enters the bulk tank must be from cows that are not visibly ill, indicating that before the milk is stored a general health check has to be performed. 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.

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

Acknowledgements

The authors are grateful to H. Wilhelm Schaumann foundation for financial support to this project. The technical assistance provided by the staff of the research farm Karkendamm (Kiel, Germany) is also gratefully acknowledged.

References


Chapter Two:

Mastitis detection in dairy cows by application of Fuzzy Logic

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Abstract

The aim of the present research was to develop a fuzzy logic model for classification and control of mastitis for cows milked in an automatic milking system. Recording of data was performed on the University of Kiel’s experimental dairy farm “Karkendamm”. A data set of 403,537 milkings from 478 cows was used. Mastitis was determined according to three different definitions: udder treatments (1), udder treatment or somatic cell counts (SCC) over 100,000/ml (2) and udder treatment or SCC over 400,000/ml (3). Mastitis alerts were generated by a fuzzy logic model using electrical conductivity, milk production rate and milk flow rate as input data. To develop and verify the model, the dataset was randomly divided into training data (284,669 milkings from 319 cows) and test data (135,414 milkings from 159 cows). The evaluation of the model was carried out according to sensitivity, specificity and error rate. If the block-sensitivity was set to be at least 80%, the specificities ranged between 93.9% and 75.8% and the error rate varied between 95.5% and 41.9% depending on mastitis definition. Additionally, the average number of true positive cows per day ranged from 0.1 to 7.2, and the average number of false negative positive cows per day ranged from 2.4 to 5.2 in an average herd size for the test data of 39.7 cows per day. The results of the test data verified those of the training data, indicating that the model could be generalized.

Fuzzy logic is a useful tool to develop a detection model for mastitis. A noticeable decrease in the error rate can be made possible by means of more informative parameters.

Keywords: dairy cow, mastitis, automatic milking, fuzzy logic.
1. Introduction

Mastitis is the most costly disease in dairy cattle today and remains one of the major problems for the dairy industry (Heald et al., 2000; Seegers et al., 2003). Average economic losses due to mastitis are estimated to be around 150 Euro per cow and year (DVG, 2002). De Mol and Ouweltjes (2001) indicated that early detection of mastitis is very important, not only because of the economic impact due to yield losses, but also because of the negative effects on the animals’ welfare. In herds with an Automatic Milking System (AMS), identification of udder infections is no longer based on visual observation. In contrast, control programmes managing the health status of the cows are introduced based on sensor measurements. Detection of mastitis can be automated by using an integrated system with sensor measurements of milk yield, milk temperature and the electrical conductivity of the milk (Frost et al., 1997). The suitability of electrical conductivity for mastitis detection has been analysed in previous research (Cavero et al., 2006). An improvement on the reported results was expected by multivariate analyses of the traits. Wendt et al. (1998) indicated the possibility of using the milk production rate as meaningful additional information to electrical conductivity to detect mastitis.

Fuzzy set theory provides a strict mathematical framework for dealing with vague conceptual phenomena to describe uncertainties in real life situations and models fuzzy relations (Zimmermann, 1991). Fuzzy logic is a well-known application method in decision support, classification and controlling processes that have no simple mathematical approach (Grauel, 1995). Fuzzy logic has already been used for oestrus detection with good results (Firk et al., 2003; Yang, 1998), moreover, it has been also used to improve sensitivity and specificity of systems using conductivity as the main information source for mastitis detection (De Mol and Woldt, 2001). Koehler and Kaufmann (2002) stated that identification of mastitis using only conventional reasoning was difficult and suggested that the use of fuzzy logic could improve the reliability of detection.

The aim of this research was to develop and test a fuzzy logic model for the detection of mastitis using electrical conductivity (EC), milk production rate and milk flow rate. Such a management aid would allow early detection of mastitis at an initial stage with minimum labour requirements.
2. Materials and Methods

2.1 Data

Data were recorded at the University of Kiel’s experimental farm Karkendamm between July 2000 and March 2004. During this period observations from 403,537 milkings were accumulated from 478 Holstein Friesian cows with a total of 645 lactations. The mean herd size was 124 cows on average per day and 85% of the cows were in the first lactation. Milking took place in an AMS with 4 boxes. The average number of milkings per cow per day was 2.4 and the 305-day milk yield was approximately 9,200 kg on average.

The data set was randomly divided into two data subsets with different cows. Two thirds of the original data were the training data, used to develop the fuzzy logic model. The other part of the data was the test data used to test whether the developed model could be generalized.

The highest value of the electrical conductivity of the milk was measured in each 200 ml of milk and an average value of the whole milking was recorded by the AMS. EC ranged between 2 and 8 mS/cm, with an average of 5.3 to 5.5 mS/cm. The milk production was defined as milk yield per milking, divided by the intervals between milking. The average milk flow rate of the whole milking was supplied by the AMS. Descriptive statistical information about the traits are shown in Table 1.

Table 1
Means ($\bar{x}$) and standard deviations (s) for the traits milk yield, milk flow rate, time between milkings and electrical conductivity.

<table>
<thead>
<tr>
<th>Trait</th>
<th>Unit</th>
<th>Number of observations</th>
<th>$\bar{x}$</th>
<th>s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Milk yield</td>
<td>kg/milking</td>
<td>390,900</td>
<td>12.4</td>
<td>4.06</td>
</tr>
<tr>
<td>Average milk flow rate</td>
<td>kg/min</td>
<td>390,694</td>
<td>2.6</td>
<td>0.92</td>
</tr>
<tr>
<td>Time between milkings</td>
<td>h</td>
<td>403,537</td>
<td>9.9</td>
<td>2.61</td>
</tr>
<tr>
<td>Milk production rate</td>
<td>kg/h</td>
<td>388,867</td>
<td>1.4</td>
<td>0.87</td>
</tr>
<tr>
<td>EC right hind quarter</td>
<td>mS/cm</td>
<td>390,288</td>
<td>5.5</td>
<td>0.58</td>
</tr>
<tr>
<td>EC left hind quarter</td>
<td>mS/cm</td>
<td>398,326</td>
<td>5.3</td>
<td>0.56</td>
</tr>
<tr>
<td>EC right front quarter</td>
<td>mS/cm</td>
<td>395,619</td>
<td>5.4</td>
<td>0.57</td>
</tr>
<tr>
<td>EC left front quarter</td>
<td>mS/cm</td>
<td>392,110</td>
<td>5.4</td>
<td>0.59</td>
</tr>
</tbody>
</table>
2.2. Mastitis definitions

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 52,535 SCC tests were carried out with 195,000 cells/ml on average. The Deutsche Veterinärmedizinische Gesellschaft e.V. (German Veterinary Medicine Association) has stated a value of 100,000 cells/ml as the threshold for mastitis (DVG, 2002). Harmon (1994) showed an SCC for uninfected cows under 200,000 cells/ml, but for first lactating cows SCC of uninfected quarters may be under 100,000 cells/ml. 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. Three variants of mastitis definition were used in this investigation:

1) Treat: treatment performed without consideration of SCC,
2) Treat+100: treatment performed and/or a SCC > 100,000 cells/ml,
3) Treat+400: treatment performed and/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 two days after and two days before, were defined according to this SCC value and the days in the middle were set to “uncertain days”.

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

Depending on the mastitis definitions, 126, 1,612 and 620 mastitis blocks were found to conform to mastitis definitions 1, 2 and 3 respectively for the training data and 70, 736 and 322 for the test data. Distributions of days of health, days of mastitis as well as averaged mastitis and healthy cows per day subject to definition of mastitis are shown in Table 2.
Table 2

Number of days of health, days of mastitis or unknown days as well as averaged mastitis and healthy cows per day according to the three different mastitis definitions considered.

<table>
<thead>
<tr>
<th>Training data</th>
<th>Days of mastitis</th>
<th>Days of health</th>
<th>Unknown</th>
<th>Mastitis cows/day</th>
<th>Healthy cows/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Treat</td>
<td>651</td>
<td>109,690</td>
<td>4,307</td>
<td>0.5</td>
<td>80.5</td>
</tr>
<tr>
<td>2) Treat+100</td>
<td>37,719</td>
<td>68,538</td>
<td>8,391</td>
<td>27.7</td>
<td>50.3</td>
</tr>
<tr>
<td>3) Treat+400</td>
<td>6,607</td>
<td>102,476</td>
<td>5,565</td>
<td>4.9</td>
<td>75.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test data</th>
<th>Days of mastitis</th>
<th>Days of health</th>
<th>Unknown</th>
<th>Mastitis cows/day</th>
<th>Healthy cows/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Treat</td>
<td>348</td>
<td>51,588</td>
<td>2,163</td>
<td>0.3</td>
<td>37.9</td>
</tr>
<tr>
<td>2) Treat+100</td>
<td>20,713</td>
<td>29,349</td>
<td>4,037</td>
<td>15.2</td>
<td>21.6</td>
</tr>
<tr>
<td>3) Treat+400</td>
<td>3,505</td>
<td>47,771</td>
<td>2,823</td>
<td>2.6</td>
<td>35.1</td>
</tr>
</tbody>
</table>

2.3 Fuzzy Logic

In this study, a multivariate model was used to improve the mastitis detection. The sensor data were the input for the fuzzy model. This system performs a combination of conditions with electrical conductivity, milk production rate, and milk flow rate using MATLAB software (MATLAB, 2003). Preparation of data and the calculation of the classification parameters were performed by using SAS (2004).

Fuzzy logic translates natural language knowledge into formal mathematical modelling, so that it is suitable for computer processing (Biewer, 1997). The basic concept underlying fuzzy logic is that of a linguistic variable, a variable whose values are words rather than numbers. Although words are less precise than numbers, their use is closer to human intuition.

Unconventional modelling methods make better use of uncertain or imprecise data and vague knowledge about model components. The fuzzy set theory is based on an extension of the classical meaning of the term “set” and formulates specific logical and arithmetical operations for processing imprecise and uncertain information (Zadeh, 1965). In contrast to common sets, where each element belongs to a set or not, fuzzy sets have a range of membership between 0 and 1. The three steps of a fuzzy logic system are the fuzzification, fuzzy inference and the defuzzification (Zimmermann, 1991):
Fuzzification

The first step is to transform the input variables into fuzzy values by the linguistic interpretation through membership functions and the grade of membership, with a range of [0,1]. Each trait is transformed into a linguistic variable.

The input values for fuzzification were the relative deviation of the traits electrical conductivity of the milk, milk production rate and milk flow between measured and estimated values performed by means of the time series method moving average with a history of ten values. In addition, the maximum value of the electrical conductivity of the milk over all quarters was used as an input variable.

To understand the concept of linguistic variable and membership function, a graphical illustration of an example of the membership functions for the trait electrical conductivity is shown in Figure 1. An electrical conductivity value of 6.0 mS/cm would result in intersections with the membership functions “middle” and “high”. The grade of membership would be 0.35 and 0.65 for the membership function “middle” and “high” respectively.

Figure 1
Membership function for the trait maximal electrical conductivity (mS/cm).

The membership functions for all the input traits are presented in Table 3. The first value in brackets indicates the value of each trait and the second value presents the corresponding degree of membership.
Table 3
Membership functions for the traits maximal electrical conductivity, deviation in electrical conductivity, deviation in milk production rate and deviation in milk flow rate.

<table>
<thead>
<tr>
<th>Trait</th>
<th>Name of function</th>
<th>Shape</th>
<th>Point of characterisation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum electrical conductivity</td>
<td>Low</td>
<td>Trapezoidal</td>
<td>(4;1)</td>
</tr>
<tr>
<td></td>
<td>Middle</td>
<td>Triangular</td>
<td>(4.75;0)</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>Trapezoidal</td>
<td>(5.5;0)</td>
</tr>
<tr>
<td>Deviation in electrical conductivity</td>
<td>Low</td>
<td>Trapezoidal</td>
<td>(0;1)</td>
</tr>
<tr>
<td></td>
<td>Middle</td>
<td>Triangular</td>
<td>(0.9;0)</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>Triangular</td>
<td>(1.05;0)</td>
</tr>
<tr>
<td></td>
<td>Very high</td>
<td>Trapezoidal</td>
<td>(1.15;0)</td>
</tr>
<tr>
<td>Deviation in milk production rate</td>
<td>Very low</td>
<td>Trapezoidal</td>
<td>(0;1)</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>Triangular</td>
<td>(0.6;0)</td>
</tr>
<tr>
<td></td>
<td>Middle</td>
<td>Triangular</td>
<td>(0.75;0)</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>Triangular</td>
<td>(1;0)</td>
</tr>
<tr>
<td></td>
<td>Very high</td>
<td>Trapezoidal</td>
<td>(1.25;0)</td>
</tr>
<tr>
<td>Deviation in milk flow rate</td>
<td>Very low</td>
<td>Trapezoidal</td>
<td>(0;1)</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>Triangular</td>
<td>(0.6;0)</td>
</tr>
<tr>
<td></td>
<td>Middle</td>
<td>Triangular</td>
<td>(0.75;0)</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>Triangular</td>
<td>(1;0)</td>
</tr>
<tr>
<td></td>
<td>Very high</td>
<td>Trapezoidal</td>
<td>(1.25;0)</td>
</tr>
</tbody>
</table>

Fuzzy inference
The linguistic combination of the traits was performed in the fuzzy inference. The rules used result from human knowledge and have the form: if condition, then conclusion. The degree to which each part of the condition has been satisfied for each rule is known by the corresponding grades of membership. The outcome of combined traits in this investigation
was the determination of the health status of the cow with the membership functions “mastitis”, “high” possibility of mastitis, “middle” possibility of mastitis, “low” possibility of mastitis and “no mastitis”. An example for a rule box for combination of the traits ‘maximal electrical conductivity’ and ‘deviation in electrical conductivity’ is presented in Table 4. For example: IF deviation in electrical conductivity is “high” AND maximal electrical conductivity is “high”, THEN health status is “high” possibility of mastitis.

Table 4
Rules for the fuzzy inference for the traits maximal electrical conductivity and deviation in electrical conductivity.

<table>
<thead>
<tr>
<th>Deviation in electrical conductivity</th>
<th>Maximum electrical conductivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Middle</td>
<td>No mastitis</td>
</tr>
<tr>
<td>High</td>
<td>No mastitis</td>
</tr>
<tr>
<td>Very high</td>
<td>No mastitis</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Maximal electrical conductivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
</tr>
<tr>
<td>Middle</td>
</tr>
<tr>
<td>High</td>
</tr>
<tr>
<td>Very high</td>
</tr>
</tbody>
</table>

By defuzzification, fuzzy values were transformed into a single number, representing the real variable, e.g. whether a cow suffers from mastitis or not. The grades of membership, calculated in the fuzzification step, and the rules of inference determined special areas below the membership functions of the output variable. By calculation of the centre of gravity of these areas, the fuzzy values are transformed back in order to resolve a single output value from the set.

2.4. Test procedure

The system provided an alert signal when the resulting value of defuzzification exceeded a given threshold value which depended on mastitis definition. 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.

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

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

$$sensitivity = \frac{true\ positive}{true\ positive + false\ negative} \times 100$$

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

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

$$specificity = \frac{true\ negative}{true\ negative + false\ positive} \times 100$$

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

$$error\ rate = \frac{false\ positive}{false\ positive + true\ positive} \times 100$$

In addition, the number of false positive and true positive cows per day is given as well. The number of false positive cows per day is quite important. True positive and false positive cows/day signifies the average number of rightly and wrongly diseased-registered cows per day respectively and thus directly indicates the effort of the farmer with regard to mastitis monitoring.

3. Results and discussion

The aim of using training data was to develop a fuzzy logic 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, 2000). Therefore, the block-sensitivity was set to be at least 80%, thus the threshold for the value of fuzzy output for the alarm occurrence was optimised for each variant. The parameters specificity and error rate were applied for evaluation of the reliability of the detection model.
As shown in Table 5, the specificities were high with 94.0%, 77.5% and 89.1% for Variants 1, 2 and 3 respectively. However, error rates were also high ranging between 96.1% and 46.5%. The fact that there are many more “days of health” than “days of mastitis” causes a greater likelihood for FP to arise, which has an impact on the error rate, especially in the first mastitis definition (Treat).

Table 5
Classification parameters of mastitis detection from the training data and test data by the fuzzy logic models using the information electrical conductivity, milk yield, milk flow and time between milkings.

<table>
<thead>
<tr>
<th></th>
<th>Threshold</th>
<th>Block-sensitivity</th>
<th>Specificity</th>
<th>Error rate</th>
<th>TP cows/day</th>
<th>FP cows/day</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Training data</strong></td>
<td>1) Treat</td>
<td>0.64</td>
<td>81.1</td>
<td>94.0</td>
<td>96.1</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2) Treat+100</td>
<td>0.36</td>
<td>80.1</td>
<td>77.5</td>
<td>46.5</td>
<td>12.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3) Treat+400</td>
<td>0.50</td>
<td>81.2</td>
<td>89.1</td>
<td>77.2</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Test data</strong></td>
<td>1) Treat</td>
<td>0.64</td>
<td>92.9</td>
<td>93.9</td>
<td>95.5</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2) Treat+100</td>
<td>0.36</td>
<td>83.2</td>
<td>75.8</td>
<td>41.9</td>
<td>7.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3) Treat+400</td>
<td>0.50</td>
<td>83.9</td>
<td>88.1</td>
<td>75.7</td>
<td>1.3</td>
</tr>
</tbody>
</table>

Averaged true positive and false negative cows/day were also determined, which means the number of cows per day classified rightly and wrongly as diseased respectively, and thus directly illustrates the farmers’ effort with regard to mastitis monitoring. The number of TP cows/day for the training data were 0.2, 12.9 and 2.4 and the FP cows/day were 4.8, 10.2 and 8.0 for variants 1, 2 and 3, respectively. The average herd size for the training data was 84.2 cows/day.

The results obtained for the test data were in the same order of magnitude as for the training data (Table 5), which argue for the validation of the model and ensure that the model does not overfit the data. This may indicate that the model is generally applicable.

Three variants of mastitis definition were used in this investigation. The main disadvantage in Variant 1 (Treat) is that there may be cows which are ill but not considered as such. This results in a higher probability of FP since there may be alarms although the cows may not be
considered ill, therefore, resulting in high error rates. Moreover, there is also a higher probability of TN since fewer cows are considered ill, most negatives are true. Consequently, the specificity is also high for this variant. Variant 2 (Treat+100), with the SCC threshold recommended by the DVG (2002), is the most stringent definition. Cows with relatively low cell counts are considered to have mastitis, that is, the proportion of ill cows is high. This means a high proportion of TP, leading to a relatively low error rate. Since the proportion of healthy cows is low, the probability of TN is low and therefore the specificity is low in this variant. The third variant could be discussed as an intermediate case.

To make management decisions about cows suffering from mastitis a threshold must be set, which will separate infected cows from those free of infection. Unfortunately, the range of SCC observed in cows with mastitis and without mastitis overlap, thus it is impossible to select a single threshold which clearly distinguishes between healthy and infected cows (Dohoo, 2001). An SCC limit of 100,000 cells/ml is generally suggested for a healthy quarter (Hillerton, 1999). Others have proposed a limit of 200,000 cells/ml between healthy and diseased (Pyörälä, 2003). The area between 100,000 and 400,000 cells/ml may be considered as a grey area (Hillerton, 1999). Windig et al. (2005) established cows (heifers) having SCC under 150,000 (100,000) as healthy and SCC above 400,000 as diseased. Accordingly, in the present study the two extreme SCCs were chosen as thresholds. The choice of the threshold value for SCC is of crucial importance because it affects the proportion of correct and incorrect alarms.

The basis for the evaluation of the performance of mastitis detection is the knowledge of the actual status of the cow on each day of observation, therefore the choice of the length of the reference mastitis block is crucial. The block-sensitivity was calculated for the first five days of the mastitis block. The length of the block was chosen because an early detection of the disease is critical and weekly SCC was available, moreover, because more variable variations occur in the first few days. Therefore, the block-sensitivity was considered more relevant than the sensitivity, which was calculated for each day of the disease period. The evaluation parameters depend strongly on the length of the reference period around the date established for a case of mastitis. In fact, the block-sensitivity would increase significantly if longer periods were considered. For instance, Mele et al. (2001) took 7 days for clinical and 10 days after and 10 days before for subclinical mastitis and De Mol et al. (1997) took 10 days before till 7 days afterwards for clinical mastitis and 14 days before and after for subclinical mastitis. Specificity and error rate obtained with fuzzy logic in the current research were better than those estimated with univariate methods (Cavero et al., 2006). In that study, for a block-
sensitivity of about 80%, the specificity was 73% and the error rate was 56.2% for Variant 2 (Treat+100) and a specificity of 85% and an error rate of 81.4% for Variant 3 (Treat+400).

4. Conclusion

The automation of the detection of mastitis in farms with AMS can be a promising alternative to visual observation. Fuzzy logic was used to develop a detection model for mastitis that can be used in the future to support the management decision of the farmer. The application of fuzzy logic gives the model the advantage of being easy to interpret, easy to modify and adapt, by changing the membership functions and the bases of the rules. The main problem of developing the fuzzy logic models will always be the appropriate choice of suitable membership functions and set of rules. To-date there are no standard methods available to transform human knowledge and experience into rule bases. The optimal design therefore was found by trial-and-error attempts. With fuzzy logic models, better results are found than with the univariate methods. Nevertheless the error rates are high.

A noticeable decrease in the error rate is possible by means of more informative parameters. This could be achieved by improvement of sensor technology, and by the implementation of more explanatory traits.

References


Chapter Three:

Mastitis detection in dairy cows by application of Neural Networks

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Abstract

The aim of the present research was to investigate the usefulness of neural networks (NN) in the early detection and control of mastitis in cows milked in an automatic milking system. A data set of 403,537 milkings involving 478 cows was used. Mastitis was determined according to two different definitions: udder treatment or somatic cell counts (SCC) over 100,000/ml (1) and udder treatment or SCC over 400,000/ml (2). Mastitis alerts were generated by a NN model using electrical conductivity, milk production rate, milk flow rate and days in milk as input data. To develop and verify the model, the dataset was randomly divided into training and test data subsets. The evaluation of the model was carried out according to block-sensitivity, specificity and error rate. When the block-sensitivity was set to be at least 80%, the specificities were 51.1% and 74.9% and the error rates were 51.3% and 80.5% for mastitis definitions 1 and 2, respectively. Additionally, the average number of true positive cows per day ranged from 1.2 to 6.4, and the average number of false negative positive cows per day ranged from 5.2 to 6.8 in an average herd size of 24 cows per day for the test data. The results for the test data verified those for the training data, indicating that the model could be generalized.

NN is a useful tool to develop a detection model for mastitis. A noticeable decrease in the error rate could be achieved by means of more informative parameters.

Keywords: dairy cow, mastitis, automatic milking, decision aid, neural networks.
1. Introduction

Mastitis is the most costly disease in dairy farming today and remains one of the major problems concerning the dairy industry (Heald et al., 2000; Heringstad et al, 2000; Seegers et al., 2003). Barkema et al. (1998) found mean infection rates of clinical mastitis of 25-30%. Average economic losses due to mastitis are estimated to be around 150 Euro per cow and year (DVG, 2002). Early detection of mastitis would reduce milk yield losses (Nielen et al., 1995a, 1995b). Moreover, early treatment has significantly limited the severity of the disease and, in many cases, prevented the appearance of clinical cases (Milner et al., 1997). To sum up, early detection of mastitis is very important, not only because of the reduction of the economic impact, but also because of the benefits to the animals’ welfare (De Mol et al., 1999).

In herds with an Automatic Milking System (AMS), identification of udder infections is no longer based on visual observation. In contrast, control programs managing the health status of the cows have been introduced, based on sensor measurements. The detection model should generate alerts for mastitis that are meant to draw the attention of the farmer to a cow that may be ill (De Mol 1999). Detection of mastitis can be automated by using an integrated system with sensor measurements of milk yield, milk temperature and the electrical conductivity of the milk (Frost et al., 1997). Mottram (1997) argued that the future development of dairy farms as efficient producers of good quality milk from healthy cows depends on the advancement of disease detection, whereby monitoring systems would play an increasingly important part in that process.

The suitability of electrical conductivity (EC) for mastitis detection has been widely analysed in the literature (e.g. Nielen et al., 1992; Hamann and Zecconi, 1998; Melé et al., 2001; Norberg et al., 2004 and Cavero et al., 2006b). An improvement on the reported results based on EC was expected by multivariate analyses of the traits. The traits milk production rate, milk flow and days in milk were included as meaningful extra information in addition to EC to detect mastitis.

As the prediction of mastitis is complex and non-linear, classical statistical tools are not appropriate. The application of artificial intelligence techniques is therefore proposed for the development of a mastitis detection model. Neural Networks (NN) were adopted based on the inherent ability of learning algorithms to detect pattern in data. A NN is a system that is designed to model the way the brain performs a particular task. A NN consists of layers of highly interconnected processing units (neurons). Knowledge is acquired by the network from the data through a learning process. Interneuron connection strength (synaptic weights) is
used to store the knowledge acquired (Haykin, 1999). Multiple layers with non-linear transfer function allow the network to learn linear and non-linear relationships between model inputs and outputs.

NNs are widely used in medicine. In agricultural, NNs have been used successfully in different fields as well. Hill (2000) used a NN to predict and classify beef tenderness. NNs were also used in milk yield predictions (Lacroix et al., 1997; Salehi et al., 1998). In the field of control and monitoring, Krieter et al. (2006) applied a NN for oestrus detection. Yang et al. (2000) used a NN to identify the main factors associated with the presence or absence of mastitis. Moreover, attempts to develop a model to detect and classify mastitis have also been carried out, based on NNs (Heald et al., 2000; Nielen et al. 1995a, 1995b).

The aim of the present paper is to describe an NN using electrical conductivity (EC), milk production rate, milk flow and days in milk. Such a management aid would allow early detection of mastitis at an initial stage with minimum labour requirements.

2. Materials and Methods

2.1 Data

Data were recorded at the University of Kiel’s experimental farm Karkendamm between July 2000 and March 2004. During this period observations from 403,537 milkings were accumulated from 478 Holstein Friesian cows with a total sum of 645 lactations, the average herd size was 124 cows per day. Milking took place in an AMS with 4 boxes. The average number of milkings per cow per day was 2.4 and the 305-day milk yield was approximately 9,200 kg on average.

The AMS measured the highest value of the EC of the milk every 200 ml for each udder-quarter and at the end of the milking the average value of the whole milking was recorded by the AMS. EC ranged between 2 and 8 mS/cm, with an average of 5.3 to 5.5 mS/cm. The milk production rate was defined as milk yield per milking, divided by the respective milking interval. The trait average milk flow rate of the whole milking was supplied by the AMS. Descriptive statistical information about the traits is shown in Table 1.
Table 1

Means (\(\bar{x}\)) and standard deviations (s) for the traits milk yield, milk flow rate, time between milkings and electrical conductivity.

<table>
<thead>
<tr>
<th>Trait</th>
<th>Unit</th>
<th>Number of observations</th>
<th>(\bar{x})</th>
<th>s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Milk yield</td>
<td>kg/milking</td>
<td>390,900</td>
<td>12.4</td>
<td>4.06</td>
</tr>
<tr>
<td>Average milk flow rate</td>
<td>kg/min</td>
<td>390,694</td>
<td>2.6</td>
<td>0.92</td>
</tr>
<tr>
<td>Time between milkings</td>
<td>h</td>
<td>403,537</td>
<td>9.9</td>
<td>2.61</td>
</tr>
<tr>
<td>Milk production rate</td>
<td>kg/h</td>
<td>388,867</td>
<td>1.4</td>
<td>0.87</td>
</tr>
<tr>
<td>EC right hind quarter</td>
<td>mS/cm</td>
<td>390,288</td>
<td>5.5</td>
<td>0.58</td>
</tr>
<tr>
<td>EC left hind quarter</td>
<td>mS/cm</td>
<td>398,326</td>
<td>5.3</td>
<td>0.56</td>
</tr>
<tr>
<td>EC right front quarter</td>
<td>mS/cm</td>
<td>395,619</td>
<td>5.4</td>
<td>0.57</td>
</tr>
<tr>
<td>EC left front quarter</td>
<td>mS/cm</td>
<td>392,110</td>
<td>5.4</td>
<td>0.59</td>
</tr>
</tbody>
</table>

2.2. Mastitis definitions

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 52,535 SCC tests were carried out with 195,000 cells/ml on average. The Deutsche Veterinärmédizinische Gesellschaft e.V. (German Veterinary Medicine Association) 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. Also two variants of mastitis definition were used in this investigation:

1) Treat+100: treatment performed and/or a SCC > 100,000 cells/ml,
2) Treat+400: treatment performed and/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 two days after and two days before were defined according to this SCC value and the days in the middle were set to “uncertain days”.

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

Depending on the mastitis definitions, 2,348 and 942 mastitis blocks were found in the data material which correspond to mastitis definitions 1 and 2, respectively. Distributions of days of health, days of mastitis as well as averaged mastitis and healthy cows per day, subject to definition of mastitis are shown in Table 2.

Table 2
Number of days of health, days of mastitis or unknown days as well as averaged mastitis and healthy cows per day according to the two different mastitis definitions considered.

<table>
<thead>
<tr>
<th></th>
<th>Days of mastitis</th>
<th>Days of health</th>
<th>Unknown</th>
<th>Mastitis cows/day</th>
<th>Healthy cows/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Treat+100</td>
<td>58,432</td>
<td>97,887</td>
<td>12,428</td>
<td>42.9</td>
<td>71.9</td>
</tr>
<tr>
<td>2) Treat+400</td>
<td>10,112</td>
<td>150,247</td>
<td>8,388</td>
<td>7.5</td>
<td>110.3</td>
</tr>
</tbody>
</table>

2.3 Neural Networks

The technique of Neuronal Networks was developed in the field of artificial intelligence to emulate a biological neural net in the human brain as an information processing system. It is a massively parallel distributed processor made up of simple processing units, called neurons (computation nodes).

There is a great variety of NN. They differ in the distribution and the interconnections between neurons. In this study, the multilayer feedforward network was used, where the neurons are organized in the form of layers. In these networks there is an input layer of source nodes that projects onto the next layer of neurons. In the input layer no computation is performed. The output layer generates a response to a given input. Between both the external input and the network output one or more intermediate layers of neurons exists. These layers are called hidden layers because they have no direct representation in reality, and most of the actual processing occurs there. The structure of the hidden layers can vary in terms of both the
number of hidden layers and the number of neurons therein. In the feedforward networks, each layer has as its inputs only the output signals of the preceding layer. A multilayer feedforward neural network for the case of a single hidden layer is illustrated in Fig. 1.

![Feedforward Neural Network](image)

**Figure 1**
Feedforward Neural network structure with a single hidden layer of neurons.

The neural network is fully connected, since every node in each layer is connected to every other node in the next layer. These connections are weighted, so that the signal propagates and is intensified or attenuated as in the nervous system. Each node of the hidden and output layers sums the weighted signals of the previous nodes and a bias, then the transmission of the resulting signal to the following nodes is supplied by a non-linear function called the
activation function. The activation limits the amplitude range of the output signal. In this study the hyperbolic tangent function was applied, which is known as one of the most widely used activation functions.

\[ f(X) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \]

The input X of the equation is the sum of the weighted outputs of all the nodes in the previous layer added with a bias (Fig. 2). More details of NN modelling can be found in Haykin (1999), Patterson (1997) and Rojas (1996).

Once the network weights and biases have been initialised, the network has to be trained. The learning process is called “supervised” because pairs of inputs and outputs that represent knowledge about the environment of interest are provided to the NN in the training set. After presenting the input pattern to the input layer the signal propagates through the network up to the output layer where the network yields an output (forward propagation). The calculated output value is compared to the required output. Depending on the difference between both mentioned outputs, the network adjusts the synaptic weights and biases. During training, the weights and biases of the network are iteratively adjusted to minimize a given error function between the desired response and the actual response of the network.

The back-propagation training algorithm is one of the most wide-spread algorithms for the training of the multilayer perceptron. This algorithm is based on the error-correction learning rule. During the forward propagation through the network, the synaptic weights of the
network are all fixed. During the back propagation on the other hand, the synaptic weights are all adjusted in accordance with an error-correction rule. The resilient back-propagation algorithm was used in this study for the training process. The back-propagation algorithm was stopped when the absolute rate of change in the averaged squared error per iteration was small enough ($10^{-5}$), or the maximum number of epochs was reached (300 epochs).

Figure 3 shows the changes in the mean squared error for a selected training set according to the number of epochs. An epoch is defined as a presentation of all the patterns to the network with the resulting changes in weights and biases. The error reduces quickly in the early period and becomes stable at later epochs.

![Figure 3](image)

**Figure 3**
Mean squared error reduction according to epochs (approximately 300)

The input layer of the used NN had 5 nodes: the relative deviation between measured and estimated values (estimated values are performed by means of the moving average of the ten last values) of the three traits electrical conductivity of the milk, milk production rate and milk flow, as well as the maximum value of the electrical conductivity of the milk (over all quarters) and days in milk. The output layer consisted of one node, corresponding to suffering
from mastitis. Four different architectures of NN with respect to the hidden layer were studied in order to optimise the classification accuracy, so that the NN with the best results was selected. Using a notation which refers to the number of neurons in each of the input, hidden and output layers, respectively, the four structures tested were: 5-10-1, 5-20-1, 5-30-1 and a NN with two hidden layers 5-10-10-1.

2.4. Test procedure

The system provided an alert signal when the resulting output value of the NN exceeded a given threshold value which depended on mastitis definition. 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, whereas 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.

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:

\[
\text{sensitivity} = \frac{\text{true positive}}{\text{true positive} + \text{false negative}} \times 100
\]

Whereas sensitivity considers each single day of mastitis, each mastitis block was considered as a true positive case (TP) for the block sensitivity if one or more alerts were given in the first five days of this mastitis block, otherwise a false negative case (FN).

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

\[
\text{specificity} = \frac{\text{true negative}}{\text{true negative} + \text{false positive}} \times 100
\]

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

\[
\text{error rate} = \frac{\text{false positive}}{\text{false positive} + \text{true positive}} \times 100
\]
In addition, the number of false positive and true positive 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.

2.5 Test procedure

After the network was trained, the system was tested for generalisation. Moreover, instead of using all the cases to estimate the performance of the NN, the data can be partitioned in two groups, some used for designing the NN, and some for testing it. In order to avoid a possible error in the classification results in a single random partition, a multiple train-and-test is recommended. Multifold cross validation was utilized to evaluate the ability of a NN to accurately classify mastitis cases. Because of the large sample size, the available data set was divided 5-fold, which seemed to be adequate and computationally not too expensive. The model was trained on all the subsets except one, and the performance of the NN was measured by testing it on the subset left out (Fig. 4). The performance of the model is assessed by averaging sensitivity, specificity and error rate. Preparation of data and the calculation of the classification parameters in order to develop and test the NN were performed by using MATLAB software (MATLAB, 2004)

![Figure 4](image)
Illustration of the hold-out method of multifold crossvalidation for 5 subsets

3. Results and discussion

Since the output layer consisted of a single neuron that supplied a continuous output with a value between 0 and 1, a threshold value was to be established to obtain a binary output, that is, if the cow suffered from mastitis “Yes” or “No”. The objective was to develop a detection
model with sufficient accuracy. Hence the block-sensitivity in the training data was set to be at least 80%, thus, the threshold value for the outcome alarm occurrence was optimised for each variant. The parameters’ specificity and error rate were applied for evaluation of the reliability of the detection model.

All examined NN performed similarly, therefore the simplest NN structure (5-10-1) was adopted. As shown in Fig. 3, the error fell quickly in the early period and reached a steady level. Table 3 contains the main results of the NN related to the evaluation parameters. The specificities with the training sets were 61.4% and 78.3% for variants 1 (Treat+100) and 2 (Treat+400), respectively. On the other hand, error rates were 46.5% and 79.1%, respectively. The fact that there were many more “days of health” than “days of mastitis” caused a greater likelihood for FP to arise, which had an impact on the error rate.

Table 3
Average classification parameters of mastitis detection from the training and test data subsets by the neural network model using the information electrical conductivity, milk yield, milk flow and days in milk.

<table>
<thead>
<tr>
<th>Training data ¹)</th>
<th>Threshold</th>
<th>Block-sensitivity</th>
<th>Specificity</th>
<th>Error rate</th>
<th>TP cows/day</th>
<th>FP cows/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Treat+100</td>
<td>0.32</td>
<td>79.3</td>
<td>61.4</td>
<td>46.5</td>
<td>24.8</td>
<td>21.5</td>
</tr>
<tr>
<td>2) Treat+400</td>
<td>0.10</td>
<td>80.8</td>
<td>78.3</td>
<td>79.1</td>
<td>4.8</td>
<td>18.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test data ²)</th>
<th>Threshold</th>
<th>Block-sensitivity</th>
<th>Specificity</th>
<th>Error rate</th>
<th>TP cows/day</th>
<th>FP cows/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Treat+100</td>
<td>0.32</td>
<td>84.2</td>
<td>51.1</td>
<td>51.3</td>
<td>6.4</td>
<td>6.8</td>
</tr>
<tr>
<td>2) Treat+400</td>
<td>0.10</td>
<td>78.6</td>
<td>74.9</td>
<td>80.5</td>
<td>1.2</td>
<td>5.2</td>
</tr>
</tbody>
</table>

1) Average for Training data: 99 cows per day  2) Average for Test data: 25 cows per day

The performance of the model was assessed by averaging the classification parameters under validation for the test data. The specificity decreased moderately to 51.1% and 74.9% for variants 1 and 2 respectively. In turn, the error rate increased to 51.3% and 80.5%, respectively. The results obtained for the test data agreed with those calculated for the training data, so that the model generalised well.

Averaged true positive and false negative cows/day were also determined, which means the number of cows per day classified as diseased rightly and wrongly respectively, and thus directly the farmers’ effort with regard to mastitis monitoring. The number of TP cows/day
for the training data were 24.8 and 4.8 and the FP cows/day were 21.5 and 18.2 for variants 1 (Treat+100) and 2 (Treat+400), respectively. The average herd size for the training data was 99 cows/day.

In mastitis research, different definitions of mastitis are used, mostly based on SCC or bacteriological culturing or both. Two variants of mastitis definition were used in the present investigation. Variant 1 (Treat+100), with the SCC threshold recommended by the DVG (2002), is the most stringent definition. Cows with relatively low cell counts are considered to have mastitis, thus, the proportion of ill cows is high. This means a high proportion of TP, leading to a relatively low error rate. Since the proportion of healthy cows was low, the probability of TN and therefore the specificity was low in this variant. Since the sensitivity was set to be at least 80%, the effect on the specificity was reflected in a low specificity. The basis for the evaluation of the performance of automatic mastitis detection is the knowledge of the actual status of the cow on each day of observation, therefore the choice of the length of the reference mastitis block is crucial. The block-sensitivity was calculated for the first five days of the mastitis block. The length of the block was chosen because an early detection of the disease is critical and only weekly SCC was available. Moreover, in the first few days, more variable variations occur. Therefore, the block-sensitivity was considered to be more relevant than the sensitivity, which was calculated for each day of the disease period. The evaluation parameters depended strongly on the length of the reference period around the date established for a case of mastitis. In fact, the block-sensitivity would increase significantly if longer periods were considered. For instance, Mele et al. (2001) chose a period of 7 days for clinical and 10 days after and 10 days before for subclinical mastitis and De Mol et al. (1997) took 14 days before and after for subclinical mastitis and 10 days before till 7 days afterwards for clinical mastitis. In another study, the mastitis period comprised the day when clinical mastitis was recorded plus the preceding 6 days (De Mol and Outweltjes, 2001). Furthermore, in the present study, the specificity for mastitis was calculated considering all cows. This was not the case in other studies (De Mol and Ouweltjes, 2001; Mele et al., 2001) where only cows without any mastitis case during the test period were used. This meant that in the tests performed the possibility of obtaining false alarms was considerably higher. Due to the differences in mastitis definition and data properties, comparison of the model performance with other studies is complicated. However, it is possible to make a comparison with a previous study in which the applicability of a fuzzy logic model for mastitis detection was evaluated (Cavero et al., 2006a). In that study, specificity and error rate obtained with fuzzy logic could be found to be better compared to the estimates in the current research;
a block-sensitivity of about 80%, a specificity of 75.8% and an error rate of 41.9% for variant 1 (Treat+100), and a specificity of 88.1% and an error rate of 75.7% for variant 3 (Treat+400) were found.

The back-propagation algorithm used based on minimizing the cost function, defined as the sum of error squares that is averaged over the entire training set. The important property of this criterion is its generality and mathematical tractability. However, in many situations observed in practice, minimizing the cost function corresponds to optimising an intermediate quantity that is not the ultimate objective of the system, and may therefore lead to suboptimal performance (Haykin, 1999). This might be the case here, since the aim of this study was to detect a mastitis case in the first five days, and not each milking at which time the cow suffered from mastitis.

4. Conclusion

An accurate mastitis detection system is urgently needed in farms with AMS and in conventional farms with a large herd size as an alternative to laborious visual observation. A model that detects mastitis early could be used in the future to support the management decision of the farmer. A neural network model was developed for mastitis detection using days in milk and pre-processed measurements of EC, milk yield and milk flow. The NN model is easily implemented and automated using computer analysis. For a block-sensitivity set to be at least 80%, classification results for the NN model ranged between 51.1% and 74.9% for specificity, while the error rate was between 51.3% and 80.5%, depending on the definition of mastitis. Based on these results, the system could be used as a first screening tool to alert the farmer to a subgroup of cows with a higher chance of developing mastitis.

A limited number of mastitis indicators were analysed in the present study. Additional information related to mastitis would probably improve the performance of the model. For analysis of more complicated data, an NN might be preferable, because of the non-linear relations between input and output and the fact that no assumption about the distribution of the different variables should be made. To sum up, NN are useful tools for computerised decision support systems.
References


General Discussion

Introduction

Decision-making in dairy farming has become more complex because of the intensification of dairy farming and factors such as an increase in knowledge about animal management, higher quality demands by consumers, and more governmental regulations (Pietersma et al., 1998). Mastitis is an inflammation of the mammary gland and is considered the most costly disease in dairy cattle (Heringstad et al., 2000; Ruegg, 2002; Hinrichs et al., 2005). Average economic losses due to mastitis are estimated to be approximately 150 Euro cow and year (DVG, 2002). Costs due to mastitis include veterinary and treatment costs, reduced milk production during the remaining part of lactation, the loss of milk that has to be discarded due to the contamination with antibiotics, early culling, decreased milk quality and increased disease risk in the future (Heringstad et al., 2000).

Milner et al. (1997) stated the advantages of accurate early detection of diseases insofar that antibiotic therapy may be more effective, perhaps avoiding clinical disease. It may achieve a better cure, may minimise tissue damage and impact of yield and may speed up the convalescence of the cow.

The introduction of automatic milking systems in the dairy industry has involved a significant change in management tasks, since control and identification of health status of the cow can no longer be based on visual observations. Instead, monitoring systems are to be developed based on sensor measurements related to this task. Computerised information systems can potentially help the dairy producer to deal with the increased complexity of decision-making and availability of information in dairy farming (Pietersma et al., 1998).

With an AMS there is no milker present at milking and thus there is no obligatory contact between the herdsman and the cows. Consequently, decision-making during milking is no longer possible. However, sensors may be able to take over part of the monitoring work of the farmers (Hogeveen and Ouweltjes, 2003).

There is a number of parameters related to mastitis that can be automatically measured during milking. Specially the measurement of the electrical conductivity of the milk (EC) has been widely analysed to detect mastitis (e.g. Nielen et al., 1992; De Mol et al., 1997; Hamann and Zecconi, 1998; Mele et al., 2001; Pallas, 2002; Norberg et al., 2004). However, Hamann and Zecconi (1998) found that the published information on electrical conductivity as a mastitis indicator comprises very variable results. The authors reported a sensitivity for detection of clinical mastitis ranging from 33 to 95% and a specificity ranging from 71 to 100%.
Moreover, the German Veterinary Medicine Association (DVG, 2002) argued that mastitis detection based only on EC is not accurate enough, which is confirmed by Pallas (2002). Therefore, it is suggested that other parameters be used which complement each other and improve the results of the single variable models. Nielen et al. (1995b), De Mol et al. (1997) and De Mol and Ouweltjes (2001) used milk production, EC and temperature of milk for detection of clinical mastitis with promising results.

As is outlined in this paragraph, different variables and models have been used as a mastitis indicator. The fact is that at the moment no definitive model has been found that performs the difficult task of detecting mastitis perfectly. Hovinen et al. (2004) and Binda et al. (2004) concluded that the current mastitis detection systems in automatic milking systems must be improved in order to be applied efficiently.

The overall aim of this thesis was to detect and quantify variations in the serial information recorded in a management information system, to analyse the interrelationship between the different variables and mastitis and finally to develop a mastitis detection model by the application of different methods.

**Definition of mastitis**

Somatic cell count (SCC) from quarters or cow samples can be used to predict whether an intramammary infection exists in any of the four quarters (Dohoo, 2001). According to Ruegg (2002), the largest factor that influences the SCC of milk is mastitis. However, there are some problems with using composite milk SCC to identify infected cows because of the dilution of SCC values with uninfected quarters. In addition, Dohoo (2001) indicated that unfortunately it is impossible to select a single threshold of SCC which separates infected and uninfected cows clearly and without overlap.

For this study, mastitis was defined on the basis of weekly SCC, as well as information of udder treatments. For weekly SCC, the threshold of 100,000 cells/ml was used in the present study, according to the German Veterinary Medicine Association (DVG, 2002), 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 (Milchverordnung, 2004). Three variants of mastitis definition were used in this investigation:

3) **Treat**: treatment performed without consideration of SCC,
4) **Treat+100**: treatment performed or/and a SCC > 100,000 cells/ml,
5) **Treat+400**: treatment performed or/and a SCC > 400,000 cells/ml.

*This definition was used only with the fuzzy model.*
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. Additionally, mastitis block was defined as an uninterrupted sequence of “days of mastitis”. The main disadvantage of the first variant (Treat) is that there may be cows which are ill but not considered as such. This results in a higher probability of FP since there may be alarms although the cows may not be considered ill, therefore, resulting in high error rates. Moreover, there is also a higher probability of TN since fewer cows are considered ill, most negatives are true. Consequently, the specificity is also high for this variant. Variant 2 (Treat+100) with the SCC threshold recommended by the DVG (2002) is the most stringent definition. Cows with relatively low cell counts are considered to have mastitis, that is, the proportion of ill cows is high. This means a high proportion of TP, leading to a relatively low error rate. Since the proportion of healthy cows is low, the probability of TN is low and therefore the specificity is low in this variant. The third variant could be discussed as an intermediate case.

The selection of one threshold or another depends on the use of the threshold and the prevalence of mastitis in the herd.

**Assessment Criteria**

The model performance was assessed by comparing the alerts provided by the system with the actual occurrences of mastitis. An alert was given when the resulting output value of the model exceeded a given threshold. The parameters block-sensitivity, specificity and error rate were evaluated. Block-sensitivity considers whether one or more alerts were given in the first five days of the mastitis block, in accordance with the definition of mastitis.

The choice of the reference period for early detection of mastitis was subjective, but based on the length of the period between the available reference data (weekly SCC), and also on the idea of establishing a long enough period to make possible the detection of abnormalities. Therefore a period of five days was chosen. The choice of this period is crucial, since the evaluation parameters depend strongly on this task (Mele et al., 2001). In fact, the block-sensitivity would increase significantly if longer periods were considered.

Block-sensitivity and specificity are interdependent. If the threshold of a test is increased, the number of positive outcomes and thus the block-sensitivity decreases, and the specificity increases and vice versa. Therefore, thresholds have to be set in such a way that an optimal sensitivity and specificity are reached. In the univariate analysis, the threshold was set as the
relative deviation between the actual observation and the estimated value given as a percentage. The objective was to develop a detection model with sufficient accuracy. Hence, the block-sensitivity was set to be at least 80%, thus, the threshold value for the outcome alarm occurrence in the models was optimised for each variant. The parameters’ specificity and error rate were applied for evaluation of the reliability of the detection model. The error rate was always at a high level because of the low proportion days of mastitis/days of health. Therefore, this value must be seen in relation to the other parameters specificity and block-sensitivity.

In addition, the number of false positive and true positive cows per day is given. True positive and false positive cows/day mean the average number of rightly and wrongly disease-registered cows per day, respectively. The number of false positive cows per day is very important since it represents the unnecessary effort of the farmer per day with regard to mastitis monitoring i.e. the healthy cows determined as ill from the model that the farmer should additionally check per day.

**Statistical analyses**

*Univariate analyses*

In chapter one the univariate analyses were performed with the EC trait. Three time-series methods were applied: moving average, exponentially weighted moving average and LOESS. A characteristic of time series is the fact that consecutive measurements are higher-correlated. These procedures are based on the expected estimation values from the last available data, and then, they are compared with the true values. If the measured value of EC significantly deviated from the predicted value and a threshold was reached, the system supplied an alarm signal.

The moving average calculated the forecast value as the average of the last n recordings, so that each of the n-last milk EC records received the same weight. The exponentially weighted moving average introduced a weight that declined exponentially depending on the smoothing parameter ($\alpha$) with increasing time distance between historical and actual value, the nearer the measurements were, the bigger weight they obtained for the estimation. Finally, with LOESS 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. This is the more flexible model since not only the weights change for each new milking but also the
number of points used to do this estimation. The drawback of these methods is that they are not able to detect slow but continuous increases in EC.

The three univariate methods used to detect mastitis based on EC showed similar results. A decrease in block-sensitivity with increasing threshold led to a decrease in specificity. At a block-sensitivity of around 80%, the specificity was 73% and the error rate was 56.2% for Variant 2 (Treat+100) and a specificity of 85% and an error rate of 81.4% for Variant 3 (Treat+400). The number of FP cows/day were between 15 and 20 cows/day for both variants 2 and 3. The average herd size was 94 cows/day.

The results reported in chapter one are within the range of previous results (Nielen et al., 1992; De Mol et al., 1997; Hamann and Zecconi, 1998; Mele et al. 2001; Norberg et al. 2004).

Due to high error rates, EC is not suitable enough for reliable mastitis detection. Nielen et al. (1995a) asserted a possible reason for the low sensitivity of EC to detect periods of high SCC could be that both parameters are related to udder health but are less related to each other. Because the sensitivity was set to be at least 80%, this effect would be reflected in low specificity and high error rates.

**Multivariate analyses**

An improvement in the performance of the univariate model is expected under consideration of additional traits. It is general accepted that mastitis leads to decreased milk yields (De Mol et al., 1997; Heringstad et al., 2000; DVG, 2002). Wendt et al. (1998) indicated the possibility of using the milk production rate as meaningful additional information to detect mastitis. Köhler (2002) proposed milk flow rate as an additional variable for mastitis detection. Mastitis alerts were generated by multivariate models using electrical conductivity, milk production rate and milk flow rate as input data.

An approach to control and classify mastitis is provided by Artificial Intelligence. These methods might be helpful for very complex processes, when there is no simple mathematical model, for highly non-linear processes, or if the processing of expert knowledge is to be performed. Some of these methods have been used successfully for oestrus detection instead of classical statistical methods (De Mol and Woldt, 2001; Firk et al., 2003; Krieter et al., submitted) and also for mastitis detection (Heald et al., 2000; Köhler, 2000; De Mol and Woldt, 2001). Two methods from Artificial Intelligence were used in this thesis: Fuzzy Logic and Neuronal Networks.
A mastitis detection model by application of Fuzzy Logic was implemented in chapter two. Fuzzy Logic translates knowledge described with natural human language into formal mathematical modelling, so that it is suitable for computer processing (Biewer, 1997). The basic concept underlying fuzzy logic is that of a linguistic variable, a variable whose values are words rather than numbers, making their use closer to human intuition.

The fuzzy set theory is based on an extension of the classical meaning of the term “set” and formulates specific logical and arithmetical operations for processing imprecise and uncertain information (Zadeh, 1965). In contrast to common sets, where each element belongs to a set or not, fuzzy sets have a range of membership between 0 and 1, called grade of membership. The main problem with the implementation of a fuzzy model is the choice of the fuzzy variables and the determination of the membership functions (Grauel, 1995). Too strong subdivision of the fuzzy sets inhibits a smooth run of the resulting value. Otherwise, non-overlapping sets might result in abrupt changes of the resulting value (Firk, 2002). The combination of the different traits is performed using rules with the logical operators “and” and “or”. These rules result from human knowledge and have the form: if condition, then conclusion. Hence, closely connected with this question is the special skill of human reasoning to extract only the relevant information from the available information (Grauel, 1995).

Fuzzy sets are only used for internal calculations. The fuzzy outputs for all rules are finally aggregated to one fuzzy set. To obtain a crisp number without representing the real output variable, the fuzzy set has to be defuzzificated. The most widespread defuzzification method is the centre of gravity. The changes are focused on changing rules and adjusting membership functions. The application of fuzzy logic gives the model the advantage of being easy to interpret, easy to modify and adapt, by changing the membership functions and the basis of the rules. All parts of the fuzzy model are susceptible to optimisation. The main problem of developing the fuzzy logic models will always be the appropriate choice of suitable membership functions and set of rules. To date there are no standard methods available to transform human knowledge and experience into rule bases. The optimal design therefore was found by trial-and-error attempts.

The best results have been obtained by application of Fuzzy Logic with the traits electrical conductivity, milk production rate and milk flow rate. The specificities were high with 93.9%, 75.8% and 88.1% for Variants 1, 2 and 3, respectively. However, error rates were also high with 95.5%, 41.9% and 75.7% for the three variants, respectively. The number of FP
cows/day for the test data were 2.4, 5.2 and 4.1 cows/day for variants 1, 2 and 3, respectively. The average herd size for the test data was 39.7 cows/day.

The use of this model offers especially an improvement of the error rate, compares with the univariate model.

Neural Networks (NNs)

A NN is a model consisting of layers of highly interconnected processing units, called neurons. The knowledge of the model is stored in the weights of the connections and bias. In the input layer no computation is performed. The output layer generates a response to a given input. Between both the external input and the network output, one or more intermediate layers of neurons exist (hidden layers).

During training input/output patterns are presented to the model. After presenting the input pattern to the input layer the signal propagates through the network using an activation function up to the output layer, where the network yields an output. The calculated output value is compared to the required output. Depending on the difference between both mentioned outputs, the network adjusts the synaptic weights and biases (Haykin, 1999). The back-propagation algorithm is used to iteratively adjust the weights and biases in accordance with an error-correction rule. The primary advantage of using neural networks over traditional statistical models for classifying problems is that NNs can adapt or learn to improve performance (Heald et al., 2000). Additionally, these systems can be easily implemented and automated using computer analysis.

Finally, a neural network was tested with the addition of days in milk as input variable. Days in milk was included in the model because most clinical mastitis occurs in the first 50 days in milk (Klaas, 2000). The results obtained with neural networks showed a decrease in specificities to 51.1% and 74.9% for Variants 2 and 3, respectively, and an increase of the error rate to 51.3% and 80.5%, respectively. The number of FP cows/day for the test data were 6.8 and 5.2 cows/day for variants 2 and 3, respectively. The average herd size for the test data was 25 cows/day.

The worst results were obtained by using the neural network model, which might be caused by the high healthy/mastitis cows ratio in the training data sets. Overtraining can occur when certain patterns predominate. Moreover, the used back-propagation algorithm is based on minimising the cost function, defined as the sum of error squares that is averaged over the entire training set. The important property of this criterion is its generality and mathematical tractability. However, in many situations observed in practice, minimizing the cost function
corresponds to optimising an intermediate quantity that is not the ultimate objective of the system, and may therefore not lead to optimal performance (Haykin, 1999). This might be the case here, since the aim of this study was to detect a mastitis case in the first five days, and not at each milking where the cow suffered from mastitis.

Classification results

EC of milk depends on its point of measurement. EC of foremilk, before alveolar milk ejection starts, gives better information on the health status than other milk fractions (Woolford et al., 1998; Barth et al., 2000). Unfortunately, in the present study the EC was averaged across the whole quarter milk, and no measurement of foremilk was available. The traits milk production rate and milk flow rate were measured at a milking level which reduces their usefulness (De Mol, 2000). This is confirmed by Knappstein and Reichmuth (2000), who found that a combination of the parameters milk yield per hour and EC for online detection of mastitis enhanced the detection rate, however, it increased the number of false positive alarms as well. The authors suggested that the specificity may be improved by measurement of milk production at a quarter level.

Duda (1995) argued that the relationship between milk flow and udder health is weak, thus the milk flow as further input variable may not be able to provide enough additional information about udder health. Other parameters such as the length of the plateau phase (Dodenhoff et al., 1999) or the length of the descend phase (Naumann et al., 1998) are suggested as possible alternatives. Accordingly, the results obtained in chapters two and three show that the information about milk production rate and milk flow rate, in the way they were measured in this study, does not contribute much to the improvement of the model.

Comparison between investigations is difficult not only due to the different measurement technique and variables used for the evaluation, but also because of the different data material, mainly number of cows and prevalence of mastitis. Nielen et al. (1992) argued that the sensitivity is higher in herds with a high prevalence of mastitis. In this study the data were recorded at the University of Kiel’s experimental farm Karkendamm. Around 85% of the milkings are originated from cows in first lactation and the average SCC was 165,000 cells/ml, which represents a healthy herd. Moreover, the comparison between investigations is difficult because of the different definitions used for mastitis. Other mastitis definitions are found in the literature with other SCC thresholds, clinical observations or additional use of bacteriological examinations as reference data. Mastitis definition has an enormous influence on the results obtained.
The basis for the evaluation of the performance of mastitis detection is the knowledge of the actual status of the cow on each day of observation. Therefore, the choice of the length of the reference mastitis block is crucial. For instance, Mele et al. (2001) took 7 days for clinical and 10 days after and 10 days before for subclinical mastitis and De Mol et al. (1997) took 10 days before till 7 days afterwards for clinical mastitis and 14 days before and after for subclinical mastitis. In this study the length of the reference mastitis block included 5 days, from two days before until two days after a mastitis. Therefore the sensitivity is expected to be lower than in the other studies.

Furthermore, in the present study, the false positive alarms for mastitis were calculated considering all cows. This was not the case in other studies (e.g. De Mol and Ouweltjes, 2001; Mele et al., 2001) where only cows without any mastitis case during the test period were used. This meant that the possibility of obtaining false alarms was considerably higher in this study. Moreover, differences in data material between different studies, such as mastitis prevalence, make further comparison difficult. Nielen et al. (1992) assume a relationship between sensitivity and prevalence, the higher the prevalence the higher the sensitivity as well.

In general, the results obtained were acceptable, but not good enough to replace the role of the farmer in making decisions regarding mastitis monitoring. Many healthy cows were signalled as suffering from mastitis. However, these models represent a valuable tool to face the difficult task of mastitis detection. Suitable traits for automatic mastitis detection require no extra labour for collection and analysing by the farmer. Attention lists generated with these models may be very useful in helping the herdsperson to make decisions regarding mastitis monitoring.

Other approaches of the sensor technique have studied milk components that are directly or indirectly related to animal health problems. Optically based sensing systems have been used to detect clots (Maasen-Francke, 2004) or blood in milk (Espada and Vijverberg, 2002). Recently, near infrared (NIR) technology has been introduced for milk quality evaluation, mastitis detection and composition measurement (Tschenkova et al., 2000). Tschenkova et al. (2004) studied a non-invasive mastitis diagnosis based on NIR spectra of udder tissue and found high correlations (r>0.90) between the classification method and the reference data milk EC or SCC for each cow’s udder quarter.

In this context and with the increasing awareness of producers regarding animal welfare and the stricter governmental directives, the improvement of appropriate health monitoring systems in dairy farms is an essential task. In the future, reliable systems to detect mastitis will be required to support the farmer in making the correct decision. The applicability of
these systems are especially important in both AMS, where no visual control is possible, and in large dairy herds, where not enough attention can be paid to each cow. For such a system, sensors capable of accurately measuring information from different sources including animal behaviour, conformation traits, milk components and herd management, as well as efficient algorithms that combine this information should be further developed.

References


Institutes für Tierzucht und Tierhaltung des Christian-Albrechts-Universität zu Kiel; Heft 119.


General Summary

This thesis focuses on developing a computerised mastitis detection system in order to improve farm management, relating to mastitis monitoring in dairy cows. With the practical application of automatic milking systems (AMS), cows voluntarily go to be milked 24 hours a day. Human inspection to detect mastitis during milking is no longer possible. At the same time, increasing herd sizes in conventional farms also make it difficult to control mastitis. This, linked with the increasing awareness of producers regarding animal welfare and stricter governmental directives, make the improvement of appropriate health monitoring systems in dairy farms an essential task.

In addition, as a result of technical progress, more and more information obtained from sensor measurement has become available. This fact opens up the possibility of making use of this information for management systems that support the farmers. In this project an early mastitis detection system was developed by application of different procedures.

Data for the analyses were recorded using the automatic milking system in the experimental “Karkendamm” dairy farm of the University of Kiel. The traits milk yield, milk flow rate and electrical conductivity were automatically recorded during the milking. Milk yield and milk flow rate were measured at a milking level, whereas electrical conductivity was accumulated at each (udder) quarter. The reference data for incidence of mastitis were treatments and the weekly milk somatic cell count (SCC) measurements of all cows.

In the first part of the thesis the potential to detect mastitis in an automatic milking system using serial information from electrical conductivity of the milk was assessed. The time series of electrical conductivity of quarter milk were analysed to find significant deviations as a sign of mastitis. Three statistical methods were tested: (1) a moving average, (2) an exponentially weighted moving average and (3) a locally weighted regression. A comparison between the efficiency of the three time series methods was performed. 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 performance of the mastitis detection model varied depending on the threshold value. A low threshold led to a sensitivity of nearly 100%, however the specificity was only about 30% and 50% depending on the mastitis definition thus the error rate was high (about 65% and 90%). Increasing the threshold up to a sensitivity of 80% increased specificity to 73% and 81% for mastitis definition Treat+100 and
Treat+400, respectively. In this case, the error rate was slightly reduced to 55% and 83. Additionally, the average number of true positive cows per day ranged from 3 to 12 depending on mastitis definition, and the average number of false negative cows per day range from 15 to 20 in an average herd size of 94 cows per day. The three methods reported 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 and the other methods showed no advantage in relation to the moving average to detect mastitis.

The aim of the second chapter was to describe the development a fuzzy logic model for classification and control of mastitis for cows milked in an automatic milking system. Mastitis alerts were generated by a fuzzy logic model using electrical conductivity, milk production rate and milk flow rate as input data. To develop and verify the model, the dataset was randomly divided into training and test data. The evaluation of the model was carried out according to block-sensitivity, specificity and error rate. If the block-sensitivity was set to be at least 80%, the specificities were 75.8% and 88.1% and the error rate were 41.9% and 75.7% for mastitis definition Treat+100 and Treat+400, respectively. Additionally, the average number of true positive cows per day were 1.3 to 7.2, and the average number of false negative positive cows per day were 4.1 to 5.2 in an average herd size for the test data of 39.7 cows per day. Compare to the univariate analyse with electrical conductivity, an improvement in error rate is reached by application of Fuzzy Logic.

The third chapter investigated the usefulness of neural networks (NN) in the early detection and control of mastitis in cows milked in an automatic milking system. In this chapter, the days in milk trait was added. To develop and verify the model, the dataset was randomly divided into training and test-data subsets. When the block-sensitivity was set to be at least 80%, the specificities were 51.1% and 74.9% and the error rates were 51.3% and 80.5% for mastitis definition Treat+100 and Treat+400, respectively. Additionally, the average number of true positive cows per day ranged from 1.2 to 6.4, and the average number of false negative positive cows per day ranged from 5.2 to 6.8 in an average herd size for the test data of 24 cows per day. These results show the complexity of mastitis and the necessity to continue research into sensor techniques that measure more mastitis-related variables, in order to obtain reliable monitoring systems to support the farmers efficiently.
Zusammenfassung


Durch technischen Fortschritt stehen mehr und mehr Informationen aus Sensormessungen zur Verfügung. Dadurch bietet sich die Möglichkeit, diese Informationen für Managementsysteme zu nutzen und damit die Landwirte zu unterstützen. In diesem Projekt wurde unter Anwendung verschiedener Prozeduren ein Mastitisfrüherkennungssystem entwickelt.


Der erste Teil dieser Arbeit befasste sich mit der Beurteilung des Potentials zur Mastitiserkennung mit Hilfe serieller Informationen der elektrischen Leitfähigkeit. Es wurde eine Zeitreihenanalyse der elektrischen Leitfähigkeit von jedem Euterviertel vorgenommen, um signifikante Abweichungen als Hinweis für eine Mastitiserkrankung zu finden. Dabei wurden drei statistische Methoden angewendet: (1) ein „moving average“, (2) ein „exponentially weighted moving average (EWMA) und (3) eine „locally weighted regression“. Diese drei Zeitreihenanalysemethoden wurden hinsichtlich ihrer Effizienz bei der Mastitiserkennung miteinander verglichen. Ein Alarm wurde dann ausgelöst, wenn die
relative Abweichung des gemessenen Wertes vom geschätzten Wert, ausgedrückt in Prozent, eine vorher festgelegte Schwelle überschritt. Die drei unterschiedlichen Methoden lieferten ähnliche Ergebnisse hinsichtlich Sensitivität, Spezifität und Fehlerrate. Diese drei Erfolgsgrößen der Mastitiserkennungsmodelle varierten abhängig vom Schwellenwert. Ein niedriger Schwellenwert führte zu einer Sensitivität nahe 100 %, während die Spezifität, je nach Mastitisdefinition, niedrige Werte zwischen 30 % und 50 % erreichte. Infolgedessen lag auch die Fehlerrate in solchen Fällen bei 65 % bis 90 %. Ein Anheben des Schwellenwertes führte, bei dann erreichten Sensitivitäten von immer noch 80 %, zu einer Verbesserung der Spezifität auf Werte von 73 % für die Mastitisdefinition Behandlung + 100 bzw. 81 % für die Definition Behandlung + 400. Gleichzeitig konnte die Fehlerrate auf 55 % bzw. 83 % reduziert werden. Die durchschnittliche Anzahl von wahr positiven Kühen betrug dann abhängig von der Mastitisdefinition 3 bis 12, während 15 bis 20 Fälle von falsch negativen Kühen pro Tag bei einer mittleren Herdengröße von 94 Kühen auftraten. Alle drei Methoden zeigten eine gute Sensitivität und Spezifität bei einem geeigneten Schwellenwert, aber auch hohe Fehlerraten. Das moving average war in dieser Untersuchung die einfachste Methode und zeigte dennoch keine schlechteren Ergebnisse zur Mastitiserkennung im Vergleich zu den anderen Methoden.

Das Ziel des zweiten Kapitels bestand in der Entwicklung eines Fuzzy-Logic Modells zur Klassifizierung und Kontrolle von Mastitis in einem automatischen Melksystem. Mastitis-Alarme wurden durch ein Fuzzy-Logic-Modell generiert, in das die elektrische Leitfähigkeit, die Milchproduktionsrate und die Milchflussrate als Inputvariablen einflossen. Um das Modell zu entwickeln und zu verifizieren, wurde der gesamte Datensatz zufällig in einen Trainings- und einen Testdatensatz eingeteilt. Die Evaluierung des Modells wurde mit Hilfe der Parameter Blockssensitivität, Spezifität und Fehlerrate durchgeführt. Bei einer vorausgesetzten Blockssensitivität von mindestens 80 % betrug die Spezifität 75,8 % und 88,1 % für die Mastitisdefinitionen Behandlung + 100 bzw. Behandlung + 400, während die ermittelte Fehlerrate für diese Mastitisdefinitionen bei 41,9 % bzw. 75,7 % lag. Damit ergaben sich als durchschnittliche Anzahl 1,3 bzw. 7,2 wahr positive Kühe und 4,1 bzw. 5,2 falsch positive Kühe pro Tag, wobei die durchschnittliche Herde des Testdatensatzes 39,7 Kühe pro Tag umfasste. Verglichen mit den Ergebnissen der univariaten Analysen der elektrischen Leitfähigkeit, konnte eine Verbesserung in der Fehlerrate durch die Anwendung von Fuzzy-Logic erreicht werden.
Im dritten Kapitel wurde die Anwendbarkeit von neuronalen Netzen bei der Mastitisfrüherkennung in einem automatischen Melksystem untersucht. Hierfür wurde das Merkmal Laktationstag zusätzlich in das Modell aufgenommen. Um das Modell zu entwickeln und zu verifizieren, wurde wiederum der gesamte Datensatz zufällig in einen Trainings- und einen Testdatensatz eingeteilt. Bei einer erneut vorausgesetzten Blocksensitivität von mindestens 80 % konnten Spezifitäten von 51,1 % und 74,9 % sowie Fehlerraten von 51,3 % und 80,5 % für die Mastitisdefinitionen Behandlung + 100 bzw. Behandlung + 400 ermittelt werden. Hierbei ergaben sich bei einer mittleren Herdengröße des Testdatensatzes von 24 Kühen pro Tag durchschnittlich 1,2 bzw. 6,4 wahr positive Kühe und 5,2 bzw. 6,8 falsch positive Kühe für die unterschiedlichen Mastitisdefinitionen.

Resumen

La presente tesis se centra en el desarrollo de un sistema de detección automática de la mamitis, con el fin de mejorar la gestión de las operaciones relacionadas con el control de la misma en ganado vacuno de leche. Con la puesta en funcionamiento del sistema automático de ordeño, las vacas pueden acudir voluntariamente las 24 horas del día al robot para la extracción de la leche. De esta forma, la inspección humana durante el ordeño para la detección de mamitis ya no es posible. Por otra parte, el creciente tamaño de los rebaños en las explotaciones ganaderas convencionales, dificulta de igual modo la labor del control de mamitis. Este hecho, unido a su vez a la creciente sensibilización tanto de consumidores como de productores en cuestiones relacionadas con el bienestar animal y a las estrictas normativas gubernamentales, convierten la mejora y desarrollo de adecuados sistemas para el control de la salud animal en las explotaciones ganaderas en una tarea esencial.

En este contexto y gracias al progreso técnico, cada vez más información obtenida a través de sensores se encuentra disponible. Este hecho abre la posibilidad de hacer uso de esa información a través de programas de gestión con el fin de ayudar al ganadero. En este proyecto se desarrolló un sistema para la detección de la mamitis en estadios tempranos de desarrollo de la enfermedad haciendo uso de diferentes procedimientos. Los datos empleados para el análisis fueron recogidos en el robot de ordeño de la granja experimental “Karkendam” de la universidad de Kiel. Los parámetros producción de leche, tasa de flujo de leche y conductividad eléctrica de la leche fueron grabados automáticamente durante el ordeño. La producción de leche y la tasa de flujo de leche fueron obtenidas a nivel de ordeño, mientras que la conductividad eléctrica de la leche fue medida en cada cuarterón. Los parámetros de referencia para la determinación de las mamitis fueron los tratamientos sanitarios realizados y el análisis semanal de pruebas individuales de todas las vacas para el recuento de células somáticas en leche (S.C.C. = Somatic Cell Count, en la lengua sajona).

En la primera parte de la tesis se evaluó el potencial de detectar la mamitis en un robot de ordeño haciendo uso de la información en serie del parámetro conductividad eléctrica de la leche. Se analizaron las series temporales de la conductividad eléctrica de la leche de cada cuarterón con el fin de registrar desviaciones significativas como un signo de mamitis. Tres métodos estadísticos de suavizado de series temporales fueron evaluados: (1) el proceso de medias móviles, (2) el proceso de medias móviles ponderadas exponencialmente y (3) el proceso de ajuste no paramétrico de regresiones localmente ponderadas. Posteriormente se
llevó a cabo una comparación entre la eficacia de los tres métodos en cuanto a la detección de la mamitis. El sistema suministraba una alarma de mamitis cuando se detectaba una desviación relativa entre el valor medido y el valor estimado superior a un determinado umbral, expresado en tanto por ciento. Los tres métodos proporcionaron similares resultados atendiendo a la sensibilidad, la especificidad y la tasa de errores. El comportamiento (los resultados) del modelo de detección de mamitis varían dependiendo del valor umbral escogido. Un umbral bajo proporcionaría una sensibilidad de casi el 100% de los casos de mamitis, sin embargo, la especificidad sería solo de un 30 a un 50 % dependiendo de la definición de la mamitis, de esta manera la tasa de error sería alta (entre 65-90%). Aumentando el umbral hasta obtener una sensibilidad del 80% aumentaba la especificidad hasta el 73 y el 81% para la definición de la mamitis basado en los tratamientos sanitarios y el número de células somáticas por encima de 100.000 y 400.000 células/ml respectivamente. En este caso la tasa de error era disminuida ligeramente hasta un 55-83%. Además para este último umbral, el número medio de vacas enfermas detectadas por día oscilaba entre 3 y 5 dependiendo de la definición de la mamitis empleada, y el número de vacas sanas que recibían una alarma variaba entre 15 y 20 vacas por día en un rebaño con una media diaria de 94 vacas. Los tres métodos mostraban una buena sensibilidad y especificidad con un apropiado valor umbral, sin embargo la tasa de errores era también alta. En este estudio el método de las medias móviles era el más sencillo y los otros métodos no ofrecían ninguna ventaja que les hiciera más aconsejables que las medias móviles en cuanto a la detección de mamitis.

El propósito del segundo capítulo fue describir el desarrollo de un modelo utilizando “Fuzzy Logic” (palabra inglesa que podría ser traducida como “lógica difusa” o de una forma más precisa “lógica de los enunciados vagos”) para la detección y control de mamitis en vacas ordeñadas en un sistema automático de ordeño. Las alertas de mamitis fueron generadas por un modelo basado en Fuzzy Logic que hacía uso de los parámetros de conductividad eléctrica, producción de leche y tasa de flujo de leche como variables de entrada. Para desarrollar y verificar el modelo, los datos fueron divididos de una forma aleatoria en dos, el grupo de datos para desarrollar el modelo y el grupo de datos para probarlo. La evaluación del modelo se llevo a cabo atendiendo a los parámetros de sensibilidad, de especificidad y la tasa de errores. Si se imponía que la sensibilidad tuviera un valor de como mínimo el 80%, las especificidades eran 75,8 y 88,1% y las tasas de errores eran 41,9 y 75,7% para las definiciones de mamitis basado en los tratamientos sanitarios y el número de células
somáticas por encima de 100.000 y 400.000 células/ml respectivamente. Además el número medio de vacas enfermas detectadas por día oscilaba entre 1,3 y 7,2 dependiendo de la definición de mamitis empleada, y el número de vacas sanas que recibían una alarma variaba entre 4,1 y 5,2 vacas por día en un rebaño con una media diaria de 39,7 vacas. Comparado con los métodos univariables que sólo utilizaban la conductividad eléctrica, utilizando el modelo basado en Fuzzy Logic se conseguía una mejora en la tasa de errores.

El tercer capítulo investigaba la utilidad de los modelos basados en redes neuronales para la detección precoz y control de mamitis en vacas ordeñadas en un sistema automático de ordeño. En este capítulo la variable días de lactación fue incluida a las utilizadas en el capítulo dos. Para desarrollar y verificar el modelo, los datos fueron divididos de una forma aleatoria en dos al igual que en el capítulo anterior, el grupo de datos para desarrollar el modelo y el grupo de datos para probarlo. Si se imponía que la sensibilidad tuviera un valor de como mínimo el 80%, las especificidades eran 51,1 y 74,9% y las tasas de errores eran 51,3 y 80,5% para las definiciones de mamitis basado en los tratamientos sanitarios y el número de células somáticas por encima de 100.000 y 400.000 células/ml respectivamente. Además el número medio de vacas enfermas detectadas por día oscilaba entre 1,2 y 6,4 dependiendo de la definición de mamitis empleada, y el número de vacas sanas que recibían una alarma variaba entre 5,2 y 6,8 vacas por día en un rebaño con una media diaria de 24 vacas.

A modo de conclusión, se puede decir que los resultados muestran la complejidad de la enfermedad mamitis y la necesidad de continuar investigando sensores que midan parámetros más estrechamente relacionados con la mamitis, con el fin de obtener sistemas fiables de control que ayuden eficazmente al ganadero.
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