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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 data set 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/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 euros 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., submitted for publication). An improvement on the

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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). Köhler 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 four boxes. The average number of milkings per cow per day was 2.4 and the 305-day milk yield was approximately 9200 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 is shown in Table 1.

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 or a SCC> 100,000 cells/ml,
(3) 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

Table 1
Means (ξ) and standard deviations (s) for the traits milk yield, milk flow rate, time between milkings and electrical conductivity (EC)

Trait	Unit	Number of observations	ξ	s
Milk yield	kg/milking	390,900	12.4	4.06
Average milk flow rate	kg/min	390,694	2.6	0.92
Time between milkings	h	403,537	9.9	2.61
Milk production rate	kg/h	388,867	1.4	0.87
EC right hind quarter	mS/cm	390,288	5.5	0.58
EC left hind quarter	mS/cm	398,326	5.3	0.56
EC right front quarter	mS/cm	395,619	5.4	0.57
EC left front quarter	mS/cm	392,110	5.4	0.59

Table 2
Number of days of health, days of mastitis or unknown days as well as mean number of mastitis and healthy cows per day (percentage of the herd size in parenthesis) according to the three different mastitis definitions considered

	Days of mastitis	Days of health	Unknown	Mastitis cows/day	Healthy cows/day
Training data					
(1) Treat	651	109,690	4307	0.5 (0.5%)	80.5 (95.6%)
(2) Treat+100	37,719	68,538	8391	27.7 (33.9%)	50.3 (59.7%)
(3) Treat+400	6607	102,476	5565	4.9 (5.8%)	75.2 (89.3%)
Test data					
(1) Treat	348	51,588	2163	0.3 (0.7%)	37.9 (95.4%)
(2) Treat+100	20,713	29,349	4037	15.2 (38.3%)	21.6 (54.4%)
(3) Treat+400	3505	47,771	2823	2.6 (6.5%)	35.1 (88.4%)

Average herd size of 84.2 and 39.7 cows/day for the training and the test data, respectively.

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

Trait	Name of function	Shape	Point of characterisation		
Maximum electrical conductivity	Low	Trapezoidal	(4;1)	(4.75;1)	(5.5;0)
	Middle	Triangular	(4.75;0)	(5.5;1)	(6.25;0)
	High	Trapezoidal	(5.5;0)	(6.25;1)	(8;1)
Deviation in electrical conductivity	Low	Trapezoidal	(0;1)	(0.9;1)	(1.05;0)
	Middle	Triangular	(0.9;0)	(1.05;1)	(1.15;0)
	High	Triangular	(1.05;0)	(1.15;1)	(1.3;0)
	Very high	Trapezoidal	(1.15;0)	(1.3;1)	(4;1)
Deviation in milk production rate	Very low	Trapezoidal	(0;1)	(0.6;1)	(0.75;0)
	Low	Triangular	(0.6;0)	(0.75;1)	(1;0)
	Middle	Triangular	(0.75;0)	(1;1)	(1.25;0)
	High	Triangular	(1;0)	(1.25;1)	(1.5;0)
	Very high	Trapezoidal	(1.25;0)	(1.5;1)	(20;1)
Deviation in milk flow rate	Very low	Trapezoidal	(0;1)	(0.6;1)	(0.75;0)
	Low	Triangular	(0.6;0)	(0.75;1)	(1;0)
	Middle	Triangular	(0.75;0)	(1;1)	(1.25;0)
	High	Triangular	(1;0)	(1.25;1)	(1.5;0)
	Very high	Trapezoidal	(1.25;0)	(1.5;1)	(20;1)

as "days of mastitis" or "days of health", respectively. In the other case, the day on which the SCC was recorded, and 2 days after and 2 days before, were defined according to this SCC value and the days in the middle were set to "uncertain days".

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

Depending on the mastitis definitions, 126, 1612 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

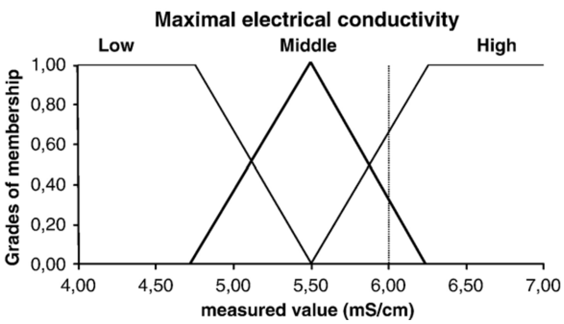

Fig. 1. Membership function for the trait maximal electrical conductivity (mS/cm).

mastitis and healthy cows per day subject to definition of mastitis are shown in Table 2.

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,

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

		Maximum electrical conductivity		
		Low	Middle	High
Deviation in electrical conductivity	Low	No mastitis	No mastitis	No mastitis
	Middle	No mastitis	No mastitis	Low
	High	No mastitis	Low	High
	Very high	No mastitis	Middle	Mastitis

fuzzy inference and the defuzzification (Zimmermann, 1991).

2.3.1. 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 10 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 Fig. 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. 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.

2.3.2. 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.

2.3.3. Defuzzification

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:

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

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 5 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:

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

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

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

In addition, the number of false positive and true positive cows per day is given as well. The number of false positive cows per day is quite important. True positive and false positive cows per 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).

Averaged true positive and false negative cows per 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 per day for the training data were 0.2, 12.9 and 2.4, and the FP cows per 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

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

	Threshold	Block-sensitivity	Specificity	Error rate	TP cows/day	FP cows/day
Training data						
(1) Treat	0.64	81.1	94.0	96.1	0.2	4.8
(2) Treat+100	0.36	80.1	77.5	46.5	12.9	10.2
(3) Treat+400	0.50	81.2	89.1	77.2	2.4	8.0
Test data						
(1) Treat	0.64	92.9	93.9	95.5	0.1	2.4
(2) Treat+100	0.36	83.2	75.8	41.9	7.2	5.2
(3) Treat+400	0.50	83.9	88.1	75.7	1.3	4.1

Average herd size of 84.2 and 39.7 cows for the training data and the test data, respectively.

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 5 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., submitted for publication). 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.

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