

On-Line Detection of Mastitis in Dairy Herds Using Artificial Neural Networks

¹E. Wang and S. Samarasinghe

¹Centre for Advanced Computational Solutions (C-fACS), Lincoln University, Canterbury, New Zealand

E-Mail: sandhya@lincoln.ac.nz

Keywords: *Artificial neural networks; SOM; Mastitis; Principle component analysis.*

EXTENDED ABSTRACT

Mastitis, one of the most significant diseases in dairy herds, is a highly complex sequence of events with various biological causes and associated physiological and behavioral effects that occur as bacterial infection progresses. The aim of the research is to develop a model for on-line detection of mastitis for robotic milking stations.

The data include milking data collected over a four month time period by robots on four farms and monthly test-day milk data collected by veterinarian for determination of the incidence of clinical mastitis (i.e. healthy cows and sick cows). A major part of work involved data pre-processing that plays an important role in this model development. Since the milking machine operated continually and it failed from time to time, an approach for normalizing the variables using running means for herd and individual cows over their own history of milkings was used. The effect of biological differences on milk yield between cows was dealt with using relative differences among quarters instead of absolute values. The final selected variables were normalized peak electrical conductivity (EcMax), normalized quarter yield fraction (QYF) and maximum relative deviation of EcMax values among four quarters for a cow (EcDV).

Parallel visualisation of data for each farm and combined datasets show that most of sick cows have high EcMax, high EcDV but low QYF, which was confirmed by correlation analysis. After data pre-processing, a linear discriminant function classifier was developed producing 81% accuracy for mastitic cases and 100% for healthy cases. In order to improve results, the dataset was further used for constructing artificial neural network (ANN) models. There were only 32 records for sick cows and 1026 for healthy cows corresponding to monthly veterinary diagnostic test. Due to the low number of mastitic cases, five random datasets were generated from original data

each having most of the sick cows and a randomly selected portion of healthy cows. Five NNs (5 experts) were developed from these datasets and validated. All of these had 94% classification rate for mastitic cases and 100% for healthy ones. In order to further improve classification rate of sick cows, three self-organising maps were trained with three-fold cross validation. The three maps produced 95% average classification rate for mastitic cows and 97% for healthy cows. In the next stage of research, the results will be used to make a final diagnosis with an associated probability of uncertainty.

1. INTRODUCTION

Mastitis, as one of the most costly diseases, has a great economic impact on the dairy industry. Other than the measure of the presence of pathogenic bacteria, the detection of which can be time-consuming and expensive, the change of somatic cell count (SCC) and electrical conductivity (EC) in milk have been found to be the most influential indicators and used in indirect tests for sub-clinical and clinical mastitis (Holmes et al., 2002; Nielen et al., 1995a; Nielen et al., 1995b; Whyte et al., 2003; Yang et al., 1999, 2000). Moreover, the change of milk production has also been reported to be a significant factor associated with the presence or absence of clinical mastitis (Heald, et al., 2000; Yang et al., 1999, 2000). Since EC, milk production and milk temperature can be measured easily by robotic milking devices, it is possible to develop a system that detects mastitis automatically during milking.

Due to some obvious statistical problems, such as co-linearity between subsequent measurements, unusual peak values and non-disease related fluctuations of variables (Nielen et al., 1995b) associated with automatically measured milking data, it is common to pre-process data by means of running averages of variables to account for the herd effect. Past studies (Holmes et al., 2002; Whyte et al., 2003; Woolford et al. 1998) on mastitis suggest that comparison of absolute milk EC levels should be avoided because some cows may naturally have high EC.

Artificial neural networks have been employed in recent research (Heald et al., 2000; López-Benavides, Samarasinghe, & Hickford, 2003; Nielen, Spigt et al., 1995; Yang et al., 1999) to distinguish between healthy and mastitic cows, and have performed reasonably well. As part of a project that aims to develop an on-line diagnosis system for mastitis, this paper presents some initial progress of the study.

2. OBJECTIVES

The study aims to develop a method for diagnosis of mastitis in dairy cows. The specific objectives are to analyse data collected by robotic milking stations; and to explore statistical and neural network methods for detecting mastitis, for further development into on-line diagnosis systems for robotic milking stations.

3. MATERIALS AND METHODS

3.1. Data and Variables

The data for this research were collected from four farms for the period from November 2002 to March 2003. It includes milking data measured by robots two or three times a day for each cow and monthly test-day veterinary milk data for the determination of the incidence of clinical mastitis in each cow.

The following variables were measured for each quarter of each cow during each milking that normally takes about few minutes: peak EC (EcMax), milk temperature at the peak EC, the total time milk has been seen at the quarter during a milking. The monthly veterinary data consist of California Mastitis Test (CMT) scores and results of the visual inspection for milk and udder, for each quarter of each cow on the test days. In this research, the quarter milk samples with a visually abnormal appearance and a CMT score that was greater than two were considered to be clinically mastitic. In contrast, the quarter milk samples with a visually normal appearance and a CMT score less than three were considered to be non-mastitic.

3.2. Preprocessing of Variables

Milk Production. Current research used the total time milk has been seen at a quarter during a milking to approximate the volume of milk produced by that quarter. For each quarter, quarter yield fraction (QYF) was defined as the ratio of milk production of a quarter in a milking to the sum of milk production of all four quarters in a milking.

The QYF was corrected based on running means of QYF in our analysis. The kernel calculation is illustrated below:

$$x_t' = x_t \times \frac{1}{a} + \left(1 - \frac{1}{a}\right) \times x_{t-1} \quad [1]$$

where

x_t' = the running mean of QYF at time t ,

x_t = the measured QYF at time t ,

a = coefficient for the equation, and

x_{t-1} = the measured QYF at time $t - 1$.

a is an arbitrary integer value that is analogous to the size of a "sliding window." To smooth the

data, two levels of QYF running mean were calculated:

- The running mean of QYF for herd. In our research, the value of a was chosen as 50 for this level. Thus, the herd running mean of QYF of the right-front quarter at milking t , for example, approximates the average of the all right-front quarter QYF values through milking ($t-50$) to milking t .
- The running mean of QYF for individual cows over their own history of milking. For this analysis, a value of 3 was adapted.

The new variable normalized QYF (NM QYF) was calculated for each quarter of each cow at each milking by dividing the cow QYF running mean over its corresponding herd QYF running mean at the milking.

Electrical Conductivity. The pre-processing of EcMax followed the same procedure as that for milk production. The only difference was x referred to the running mean of EcMax, instead of QYF, in Eq. 1. Running means of EcMax were calculated at herd level and cow level, respectively, for each quarter of each cow at each milking. Normalized EcMax (NM EcMax) was the cow EcMax running mean divided by its corresponding herd EcMax running mean. Relative deviation of EcMax (EcDv) within quarters for each cow at each milking was introduced to take into account any biological differences between cows. It was calculated as follows:

$$EcDv_i = \frac{NMEcMax_i - NMEcMax_{\min}}{NMEcMax_{\min}} \quad [2]$$

where $EcDv_i$ is EcDv of any of the four quarters of a cow, $NMEcMax_i$ is normalized EcMax of the same quarter, and $NMEcMax_{\min}$ is the smallest value of normalized EcMax between four quarters.

After the data preprocessing, robotic milking data corresponding to monthly veterinary test data were extracted to develop a new database for the analysis. The resulting data set had 32 records indicating clinical mastitis cases and 1026 indicating non-mastitis cases, according to the monthly veterinary test.

3.3. Analysis

Analysis consists of two stages: statistical data preprocessing and model development. In preprocessing stage, parallel visualization and correlation analysis were done to explore relationships and trends. Principle component analysis was conducted for removing multicollinearity and more efficient separating of mastitis cases. In modeling stage, three kinds of classifier were applied and their results were compared. Traditional linear discriminant analysis was used to test if patterns in the data could be linearly separated. Two variations of ANN, the multilayer perceptron (MLP) and the self-organizing map (SOM) were trained to detect the presence or absence of clinical mastitis. These two stages are described in detail next.

4. RESULTS AND DISCUSSION

Statistical and visualization methods of data analysis were performed on the resulting data set for inspection of natures of the variables, such as data distribution and correlation, with respect to mastitis status (i.e. healthy and clinical mastitic). Data for each farm and combined dataset (total of 5 data sets) were plotted by using parallel visualization on Xmdv Tool 6.0a, which visualizes multivariate data on a 2-dimensional space by representing each variable as a ranged bar and putting them next to each other.

Parallel visualization of the combined dataset, presented in Figure 1, shows that most of mastitic cows have high EcMax, high EcDv but low QYF, while relationships between these variables for healthy cows are even more distinct.

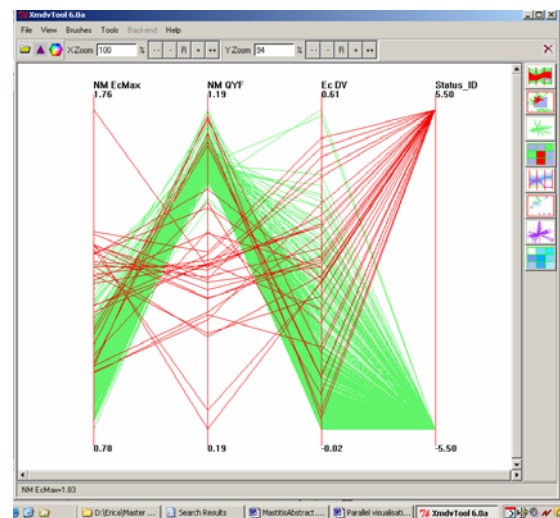


Figure 1. Parallel visualization of the combined data set. Status_ID value of 5.00 represents mastitic case and -5.00 represents healthy case.

The visualization results are consistent with correlation analysis in which NM EcMax and EcDv was found to have a positive relationship with mastitis status whereas NM QYF had a negative relationship with mastitis status. These correlation values are 0.49, 0.41 and -0.73, respectively. Therefore, the final variables selected in the analysis for detection of mastitis were EcDv, NM QYF and NM EcMax. Milk temperature was not used as a variable for current stage of the research due to various reasons, such as the distance of the tube between teats and sensors affects the milk temperature and, uneven flow of milk over the sensor could also cause the milk temperature to fluctuate (Gil, 1988). Nevertheless, whether the automatically measured milk temperature could be helpful in detection of mastitis needs to be further investigated.

To remove multi-collinearity and further differentiate mastitic cases from non-mastitic cases during milking, principle component analysis (PCA) was examined for predictive variables in classification of healthy and mastitic patterns. Kettaneh et al. (2005) find that this method has certain ability in reducing overlapping inside clusters.

Figure 2 shows the matrix plots for NM Max, NM QYF and EcDv, The plots of PCs against each other can be seen in Figure 3. The two figures reveal that patterns are slightly less overlapped in PC1, PC2 and PC3 data space than in NM Max, NM QYF and EcDv data space. Therefore, PCs were used instead of original variables in developing classifiers as discussed next.

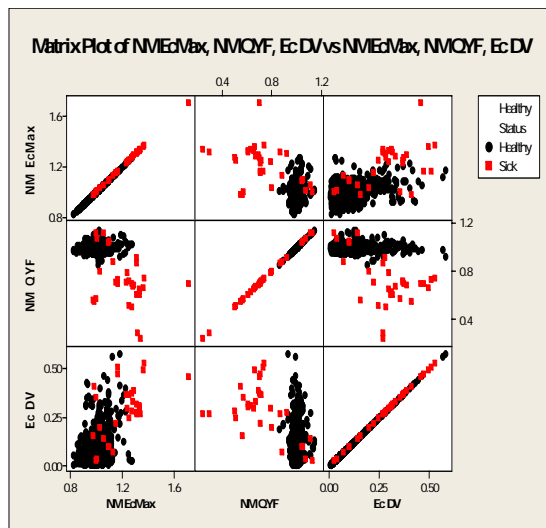


Figure 2. Matrix plot of NM Max, NM QYF and EcDv.

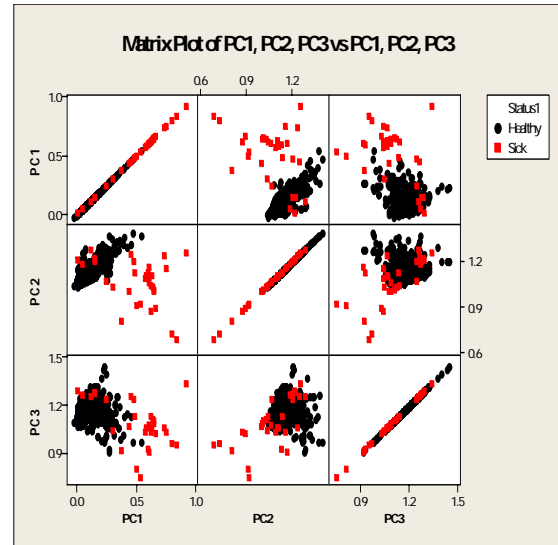


Figure 3. Matrix plot of PC1, PC2 and PC3

The results from the linear discriminant analysis shows it has a perfect detection of healthy cows with specificity (i.e. the percentage of correct identification of healthy quarters) of 100% (1026 healthy cases), while having problems with recognizing mastitic cows. Sensitivity (i.e. the percentage of correct identification of mastitic quarters) of the model is 0.81 (26 out of 32 mastitic cases). Figure 4 clearly reveals the performance of the discriminant model: the linear discriminant function boundary classifies all the healthy cases into one category but also misclassifies a few mastitic cases as healthy.

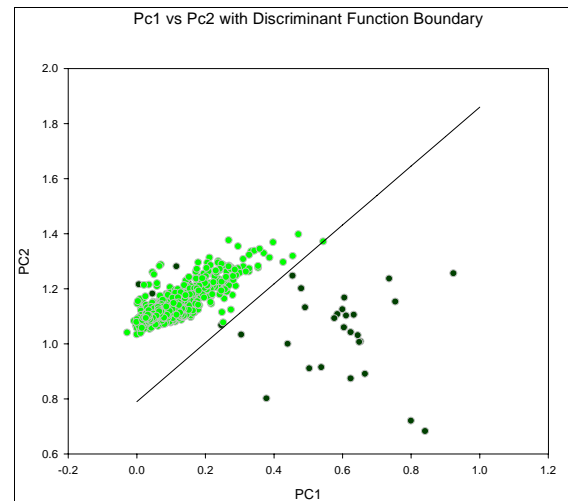


Figure 4. Plot of PC1 vs. PC2 with discriminant function boundary superimposed on it. The light points represent healthy cases; the dark points represent mastitic cases.

In order to improve the rate of detection of mastitic cases, feedforward neural networks (MLP) and

SOMs were attempted. Since there is such a low mastitis prevalence in the data set, five datasets were generated for training MLPs in the following way. The original data set was first divided into two subsets according to mastitis status of input patterns. For MLP models, 16 mastitic input patterns and 160 healthy input patterns were randomly selected to construct a training set. The corresponding test set consisted of 8 mastitic patterns randomly selected from the rest of the data in the mastitis subset and 250 healthy patterns randomly selected from the rest of the data in the healthy subset. The validation set has the same number of mastitis and healthy patterns as the test set but inputs were taken from what was left out from the two subsets. This process was repeated 5 times to obtain different randomly selected subsets of training, test and validation data to train 5 MLPs. The inputs to the networks were the three PCs. The performance of the five best trained networks to detect the incidence of mastitis in the five data sets is listed in Table 1.

Table 1. Classification results of the five best networks.

Dataset	Sensitivity	Specificity
1	0.84 (5 out of 32)	1
2	0.84	1
3	0.84	0.99 (659 out of 660)
4	0.84	1
5	0.84	1

The results show the MLPs have a better performance than the discriminant model (with a slightly improved sensitivity). On visual inspection of misclassified mastitic cases in relation to whole data, it was found that the misclassified ones are those that are closer to the healthy cases. Both MLP and discriminant classifier could not classify them correctly.

In order to improve the classification rate of mastitic cases, SOM networks of map size 12x12 were tested. The 3 data sets used for developing SOM (Kohonen, 1997) consist of a training set, which had 27 randomly extracted mastitic patterns and 50 randomly selected healthy patterns, and a test set, which had the rest of the mastitis patterns and another 50 randomly selected healthy patterns. Moreover, the mastitic patterns in the training set were repeated to increase the exposure of mastitic cases to the network. Each of trained maps was validated with all 3 validation datasets described earlier. The results from the best map producing the highest classification on validation sets are shown in Table 2.

Table 2. Classification results of the three best SOMs.

Dataset	Sensitivity	Specificity
1	0.93	0.98
2	1	0.95
3	0.93	0.97
	average = 0.95	average = 0.97

Table 2 shows that SOMs have produced much improved classification rate for mastitic cases including those that are closer to the health cases. The average classification rate for mastitic cases (sensitivity) is 95% and the rate for healthy cases (specificity) is 97%. Thus the maps have sharply differentiated the classes while projecting the input vectors onto the map creating an appropriate nonlinear boundary between healthy and mastitic cases.

The SOM projections of the individual input components and health status are shown in Figure 5. It shows that PC1 projection is very similar to health status projection. High PC1 values (darker color in the first panel) correspond to mastitic cases and darker color in status panel corresponds to mastitic cases.

The position of codebook vectors in the inputs space is presented in Figure 6. In the figure, darker nodes represent mastitic cases and lighter ones healthy cases. The figure shows that the neurons representing mastitic and healthy cases have been clustered properly in the input space. The smaller dots represent validation data.

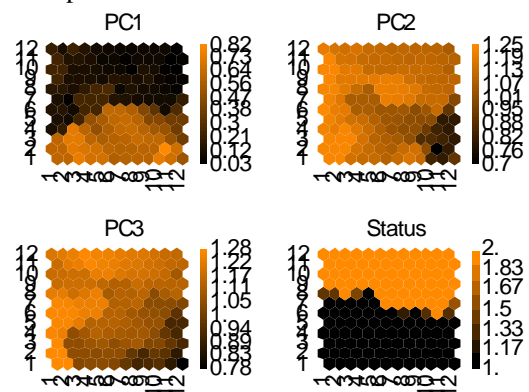


Figure 5. SOM projections with respect to PCs and health status.

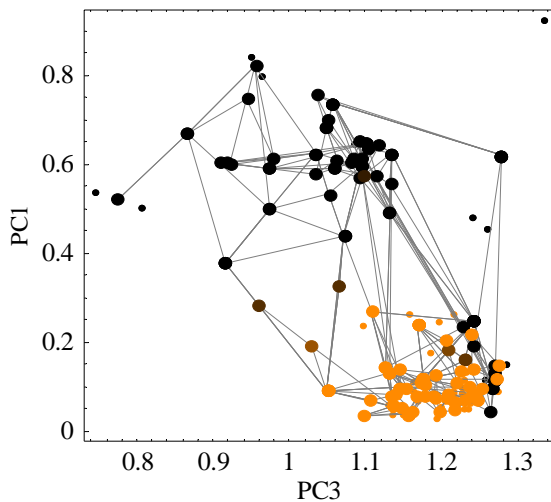


Figure 6. Codebook vectors of neurons of the trained SOM. The dark color nodes correspond to mastitic cases and the light color to healthy cases.

5. CONCLUSIONS

This paper presents the initial part of a study aimed at developing an efficient method for on-line detection of mastitis in robotic milking stations. The preprocessed data for healthy and sick cows were used on linear discriminant, MLP, and SOM classifiers. MLP results showed only a slight improvement over discriminant classifier. The MLP classified mastitis cases with 84% accuracy whereas classification rate for discriminant classifier was 81% for sick cows. Both provided 100% accuracy for healthy cows. The SOM showed much improved classification rate for mastitis cases reaching 95%; however, it slightly comprises on the accuracy of classification for healthy cows with an average rate of 97%. In the next stage of study, robustness of SOM will be further tested, the approach for making the final diagnosis will be refined, and methods for on-line map refinement will be investigated.

6. REFERENCES

- Gil, Z. (1988). Milk temperature fluctuations during milking in cows with sub-clinical mastitis. *Livest. Prod. Sci.*, 20, 223.
- Heald, C. W., Kim, T., Sisco, W. M., Cooper, J. B., & Wolfgang, D. R. (2000). A computerized mastitis decision aid using farm-based records: An artificial neural network approach. *Journal of Dairy Science*, 83(4), 711-720.
- Holmes, C. W., Brookes, I. M., Garrick, D. J., Mackenzie, D. D. S., Parkinson, T., & Wilson, G. F. (2002). *Milk production from pasture*. Palmerston North, N.Z.: Massey University.
- Kettaneh, N., Berglund, A., & Wold, S. (2005). PCA and PLS with very large data sets. *Computational Statistics & Data Analysis*, 48, 69-85.
- Kohonen, T. (1997). *Self-Organizing Maps* (Second ed.). Heidelberg, Germany: Springer-Verlag.
- López-Benavides, M. G., Samarasinghe, S., & Hickford, J. G. H. (2003). The use of artificial neural networks to diagnose mastitis in dairy cattle. Unpublished.
- Nielen, M., Schukken, Y. H., Brand, A., Deluyker, H. A., & Maatje, K. (1995a). Detection of sub-clinical mastitis from on-line milking parlor data. *Journal of Dairy Science*, 78(5), 1039-1049.
- Nielen, M., Spigt, M. H., Schukken, Y. H., Deluyker, H. A., Maatje, K., & Brand, A. (1995b). Application of a neural network to analyse on-line milking parlour data for the detection of clinical mastitis in dairy cows. *Preventive Veterinary Medicine*, 22, 15-28.
- Whyte, D., Mein, G., Claycomb, R., & Woolford, M. W. (2003). Unmasking mastitis. *Dairy Exporter*, 78(12), 92-93.
- Woolford, M. W., Williamson, J. H., & Henderson, H. V. (1998). Changes in electrical conductivity and somatic cell count between milk fractions from quarters sub-clinically infected with particular mastitis pathogens. *Journal of Dairy Research*, 65, 187-198.
- Yang, X. Z., Lacroix, R., & Wade, K. M. (1999). Neural detection of mastitis from dairy herd improvement records. *Transaction of the ASAE*, 42(4), 1063-1071.
- Yang, X. Z., Lacroix, R., & Wade, K. M. (2000). Investigation into the production and conformation traits associated with clinical mastitis using artificial neural networks. *Canadian Journal of Animal Science*, 80, 415-425.