Control Charts and Neural Networks for Oestrus Dectection in Dairy Cows

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Abstract: Exponentially weighted moving average control charts and neural networks were used for oestrus detection in dairy cows. The analysis involved 373 cows, each with one verified oestrus event. Model inputs were the traits activity, measured by pedometer, and the period (days) since last oestrus. In total 10,386 records were available, which were partitioned into training and validation subsets to train and test the neural network (multifold cross-validation). When the trained neural network was applied to the validation sets, the averaged sensitivity, specificity and error rate were 77.5, 99.6 and 9.1%, respectively. Performance for the same data with the univariate control chart was less successful. Neural networks are useful tools to improve computerised oestrus detection in dairy cows.

1 Introduction

Modern dairy farming is generally characterised by extended herd sizes and narrowed income margins per unit of output. In consequence, the economic results become more and more sensitive to minor changes in farm performance. Reproductive efficiency, e.g. oestrus detection, rebreeding and calving interval, has a strong impact on farmers' income. In order to improve oestrus detection, multivariate analyses with activity, milk yield, milk temperature, electrical conductivity and flow-rate were performed [DW01]. But none of the presented combinations showed an appreciable improvement in error rate. [Fi03] combined the trait activity and the period since last oestrus into a fuzzy logic model and observed a strong reduction in the number of false positive warnings.

The first objective of the present study was to develop a neural network model to classify oestrus alerts. The second objective of this research was to compare the classification performance of the neural network with more conventional methods from statistical quality control, i.e. control charts.

2 Material and Methods

2.1 Material

The collection of data was performed on a commercial dairy farm in 1998. During this period 373 inseminations were verified as oestrus cases by a following calving. For oestrus detection time series consisting of 15 days before oestrus, the day of oestrus and 15 days after oestrus were analysed. The trait activity was measured by conventional pedometers, which were attached to the left foreleg of each cow. The pedometers were recorded at the entrance of the rotary milking parlour. The activity values for further analyses were calculated from the difference between two successive pedometer readings, divided by the period of time between these readings. The parameter "period since last oestrus" included information about previous inseminations and previous oestrus cases. For each day considered in the analyses the period since last oestrus was calculated from the difference of the actual day and the day of previous information. Most observations accumulated around the mean oestrus cycle length of 21 days. A smaller accumulation occurred for a period of doubled oestrus cycle length.

2.1 Methods

Exponentially weighted moving-average control chart (EWMA)

A control chart is a simple time plot of a sequence of observations or subgroups statistics. The observations in the plot are compared to upper and lower control limits determining the range of variation due to common causes. If the process is in-control, nearly all observations fall between the control limits. A point outside of the control limits indicates an out-of-control signal, so more variation exits than can be attributed to the effect of common causes of variation (e.g. oestrus alert). In the present investigation, an EWMA control chart was used because it is flexible, easy to set up and operate. The EWMA is defined as

$$W_{X,t} = \lambda X_t + (1-\lambda)W_{X,t-1} \tag{1}$$

where $X_t \sim N(\mu_t, \sigma_X^2)$ and $W_{X,t}$ denotes the EWMA statistic at time t, usually $W_{X,0}$ is set equal to a target value [Mo97]. The parameter λ is a constant satisfying $0 < \lambda \leq 1$. The choice of λ determines the decline of the weights and therefore the memory of the chart. If $\lambda \to 1$, the EWMA puts all of its weight in the most recent observations. If $\lambda \to 0$, then the most recent observations are assigned a small weight and the weight attached to previous observations only slightly decreases with time.

The upper (UCL) and lower (LCL) control limits are given by

$$UCL_t, OCL_t = \mu \pm L\sigma\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2t}\right]} \tag{2}$$

The EWMA chart provides an out-of-control signal if the realisation of $W_{X,t}$ is larger then UCL_t or smaller than LCL_t. L is a constant with $L > 0$. In the present study the values of L and λ varied in order to determine the optimal performance of the control chart.

Neural networks (NN)

The Multilayer perceptron which was used in the present study is the most widely used, studied and applied NN. In these networks there is a set of input nodes (input layers), whose only role is to feed input patterns into the rest of the network. Following the input layer, and before the output layer, there are one or more intermediate layers of units. These units are called hidden units because they have no direct connection to the outside environment neither input nor output. In the feedforward networks there are no connections leading from a unit to units in a previous layer, nor to other units in the same layer nor to units more than one layer ahead. The output of every unit is connected only to the units in the next layer. Every unit is associated with a nonlinear function called the activation function. A commonly used form of nonlinearity is a sigmoid nonlinearity defined by the hyperbolic tangent. More details about the construction of NN are found in [Ha99]. Once the network weights and biases has been initialised the network has to be trained. In our study the training process followed a modified Levenberg-Marquardt algorithm (Bayesian regularisation). The backpropagation algorithm was stopped when the absolute rate of change in the averaged squared error per iteration was sufficiently small. Finally, by comparing convergence, consistency and classification accuracy, a multilayer perceptron with one hidden layer was adopted. The input layer contained two nodes (activity, days since last oestrus), the hidden layer consisted of five nodes and the output layer had only one node (oestrus event yes/no).

Evaluation and validation

The classification performance of the EWMA chart and NN can be tested by analysing the number of correctly and incorrectly classified observations: true positive (TP), false negative (FN), false positive (FP) and true negative (TN). The classification performance is expressed by the sensitivity, specificity and error rate. The sensitivity ($TP(TP+FN)^{-1}$) measures the number of correctly detected oestrus to all oestrus events. The specificity ($TN(TN+FP)^{-1}$) denotes the number of false oestrus warnings in relation to number of true negative observations. The error rate ($FP(FP+TP)^{-1}$) describes the number of false oestrus warnings in proportion to the number of detected oestrus alerts.
Multifold cross validation was used to evaluate the ability of the trained NN to accurately classify oestrus events. The available set on N (N=10,386) examples was divided into M=5 subsets. A NN model was trained on all the subsets, except for one, and the performance of the model was measured by testing it on the subset left out. The same training and validation subsets were utilised to derive the EWMA chart. The performance of the models was assessed by averaging sensitivity, specificity and error rate under training or validation over all trials of the experiment.
Preprocessing of data, deriving the EWMA control chart and building the neural network with training and validation was performed with MATLAB Version 7.0.1.24074 [Ma04].

3 Results and Discussion

Using the NN with two input nodes (activity, period since last oestrus) for oestrus detection, sensitivity was 78.7% and error rate was 5.1% with the training sets (Table 1). Specificity was always high due to the high number of true negative results. The performance of the model was assessed by averaging the classification parameter under validation. The sensitivity remained more or less constant (77.5%), but the number of false oestrus warnings in relation to the number of detected oestrus increased (9.1%).
These results confirmed that the model provided an adequate fit and generalised well. Compared to the univariate EWMA control chart with $\lambda = 0.6$ and L ranging from 2.5 to 3, sensitivity was only slightly enhanced, but an obvious improvement was found in the reduced number of false positive oestrus warnings.

	Training sets[1)]			Validation sets[1)]		
	Sensitivity	Specificity	Error rate	Sensitivity	Specificity	Error rate
Neural network	78.7	99.5	5.1	77.5	99.6	9.1
EWMA cahrt[2)]						
L = 3.0	71.3	99.3	17.1	66.9	99.3	18.8
L = 2.5	77.3	99.2	18.1	70.6	99.1	20.9

[1)] means of replications, M = 5 subsets; [2)] $\lambda = 0.60$

Table 1: Classification performance (%) of the neural network using training and validation

Using the same data set [Fi03] also observed a strong improvement in the error rate if the trait activity and period since last oestrus were combined by a fuzzy logic model (senitivity = 87.9%; error rate = 12.5%). If the input of the NN model was restricted to the trait activity, the differences between the EWMA chart and the NN model were small (sensitivity = 76.7%, error rate = 15.2% using the training set; sensitivity = 75.3%, error rate = 17.8% using the validation set) indicating the benefit of previous oestrus detection.

4 Conclusion

A neural network model was developed for oestrus detection using the activity measurements and the period since last oestrus. A feedforward three-layer perceptron provided an adequate fit and generalised well. Oestrus detection by a conventional univariate EWMA control chart was less successful.

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