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der Agrar- und Ernährungswissenschaftlichen Fakultät  
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# **Electronic monitoring of mastitis and lameness: An application and evaluation of control methods**

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# GENERAL INTRODUCTION

Modern dairy production is facing a decreasing number of farms with increasing herd size. Since one farmer has to manage an increasing number of cows, mechanisation and automation are becoming more important. As part of the work of the herdsman, monitoring the performance of dairy cows is increasingly based on automatic sensors which measure milk characteristics (e.g., yield, temperature, electrical conductivity) or activity observations (Brandt et al., 2010; Hogeveen and Ouweltjes, 2003). This development indicates a need for management support systems to be able to direct the attention of the herdsman towards those cows at the onset of mastitis or lameness.

Mastitis (inflammation of the mammary gland) and lameness are the most frequent and costly diseases in the dairy industry, in terms of economics and animal welfare (Kramer et al., 2009). Having to leave the herd prematurely due to udder diseases and lameness are rated at 16.2 % and 13.3 %, respectively (VIT, 2011). Average economic losses are estimated to be approximately 470 Euros per case of clinical mastitis (Lührmann, 2007) and more than 262 Euros per case of lameness (Ettema, 2009). Early detection of and intervention against mastitis and lameness reduces veterinary fees, losses in milk yield and milk quality, and increases the cure rate of the infected animals (Milner et al., 1997).

Several studies have attempted to develop a scheme to allow early disease detection based on cow monitoring (e.g. Caverio et al., 2007; Kramer et al., 2009; Pastell and Madsen, 2008). Due to unfavourably high numbers of cows falsely classified as ill and as a result too high error rates, none of these models have been implemented in practical monitoring (Hogeveen et al., 2010). Consequently, there is a strong need for performance improvement of the analytical detection models which translate the sensor data into information for the herdsman. Therefore, the main aim of the current study was to detect and quantify special cause variations in the serial data recorded by a management information system (milk yield, milk electrical conductivity, pedometer activity, feeding behaviour, etc.) and to finally develop an early mastitis and lameness detection system by the application of different methods.

One of the major difficulties of developing detection models is the fact that sensor data is corrupted by noise, which has a considerable influence on the characteristics of time series and by association on results of process control methods (Kamphuis et al., 2010). Wavelet

filters are able to detect and exclude noise in data (Ganesan et al., 2004; Gencay et al., 2002). Therefore, *Chapter One* investigates the applicability of wavelet filters for univariate mastitis and lameness detection based on milk electrical conductivity and pedometer activity, respectively. Classic and self-starting cumulative sum control charts were used as monitoring methods.

Mastitis and lameness are complex multifactorial diseases (Brandt et al., 2010; Chuganda et al., 2006; Hogeveen and Ouwtjes, 2003). Thus, interpretation and diagnosis of diseases is difficult if input variables are examined as though they are independent (Kourti and MacGregor, 1995). This suggests that the results of a detection model may be improved by combining all of the input variables (Cavero et al., 2008; de Mol et al., 1997; Kramer et al., 2009). Therefore, the following chapters are based on multivariate analysis.

In *Chapter Two*, principal component analysis, a latent structure method, combined with Hotelling's  $T^2$  and residual monitoring charts are applied to milking parameters, pedometer activity and feeding patterns. This monitoring system is easily implementable and effectively used for fault detection in chemical and industrial process control (Choi et al., 2005; Kourti, 2006).

The second multivariate monitoring method, called support vector machines, has recently gained attention in biomedical detection and the diagnosis of diseases (Sajda, 2006). Support vector machines, a machine-learning method, are considered to be the state-of-the-art tools for knowledge discovery and data mining in medical diagnosis (Olson and Delen, 2008). Therefore, *Chapter Three* describes the theoretical background and the applicability of support vector machines for the early detection of mastitis based on milking parameters as well as additional information, e. g., from the stage of lactation.

The final section, *Chapter Four*, again takes up the idea of cumulative sum charts and wavelet filters for mastitis and lameness detection. For this approach, the analysis focuses on multivariate cumulative sum charts. Unlike univariate control charts, multivariate cumulative sum charts take into account the relationship between the input variables of a multivariate process leading to more powerful detection algorithms (Waterhouse et al., 2010). Milk yield, milk electrical conductivity, pedometer activity and feeding patterns were used as input variables.

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# **CHAPTER ONE**

## **Detection of mastitis and lameness in dairy cows using wavelet analysis**

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## **Abstract**

The aim of this study was to explore wavelet filtering for early detection of mastitis and lameness. Data were recorded at the Karkendamm dairy research farm between January 2009 and October 2010. In total, data of 237 cows with 46,427 cow days were analysed. Mastitis was specified according to three definitions: (1) udder treatment, (2) udder treatment and/or somatic cell count with more than 100,000 cells/ml and (3) udder treatment and/or somatic cell count exceeding 400,000 cells/ml. Lameness treatments were used to determine two definitions of lameness. They differed in the length of the corresponding disease block: (1) day of treatment including three days before treatment, (2) day of treatment including five days before treatment. Milk electrical conductivity and cow activity were utilised as indicator parameters for detection of mastitis and lameness, respectively. These values were filtered by wavelets. Filtered values of cow activity and the residuals between the observed and filtered values of milk electrical conductivity were applied to a classic and a self-starting CUSUM chart to identify blocks of disease (days of disease). Regarding performance of mastitis detection, the classic chart showed better results than the self-starting chart. The block sensitivity ranged between 72.6% and 76.3% (self-starting chart between 72.1% and 74.5%) while the obtained error rates were between 69.2% and 94.4% (self-starting chart between 73.4% and 95.7%). For both charts, block sensitivity and error rate improved from definition (1) to (3). In the case of lameness detection, the block sensitivity of the classic chart varied between 40.4% and 48.3%, which was lower than the block sensitivities of the self-starting chart (47.2% and 63.5%). The error rates of lameness detection were also high (90.6% to 93.3%). In conclusion, wavelet analysis seems to be applicable to mastitis and lameness detection in dairy cows. Results could probably be enhanced if more traits for a multivariate consideration are used.

**Keywords:** mastitis detection, lameness detection, wavelet analysis, CUSUM chart

# 1 Introduction

Mastitis and lameness still remain the most frequent and costly diseases in the dairy industry, in terms of economics and animal welfare (Kramer et al., 2009). Early detection and intervention of mastitis and lameness reduces loss of milk yield, veterinary fees and loss in milk quality, and increases the cure rate of the infected animals (Milner et al., 1997). Nowadays, monitoring of animal health is increasingly based on automatic sensors that measure milk characteristics (e.g., yield, temperature, electrical conductivity) or activity observations (Brandt et al., 2010). The analysis, however, is complicated by the existence of biological variation and large intra-cow variability in such time series data (Lukas et al., 2009). Variation in observations could be interpreted incorrectly without the help of proper aids (de Vries and Reneau, 2010). The most widespread method of automatic detection of mastitis and lameness is milk electrical conductivity and cow activity, respectively (Kamphuis et al., 2008; Lukas et al., 2009). In general, changes in electrical conductivity in milk are associated with mastitis (de Mol, 2001; Lukas et al., 2009) whereas reduced activity is associated with lameness (Mazrier et al., 2006). Several studies have attempted to develop a scheme that would allow early disease detection based on cow monitoring. For mastitis detection, e.g., Kamphuis et al. (2010) used decision trees. Cavero et al. (2008) applied neural networks to monitor udder health whereas Pastell and Kujala (2007) used this method for lameness detection. Additionally, Kramer et al. (2009) exerted fuzzy logic for mastitis as well as lameness detection. Although high levels of sensitivity and specificity were reported, few of these models have been implemented in practical monitoring due to too high error rates. Additionally, a large number of false positive alerts provided by management software hinder the application in practice (Hogeveen et al., 2010). Thus, there is a strong need for performance improvement of the analytical detection models that translate the sensor data into information for the herdsmen.

One of the major difficulties of developing detection models is the fact that sensor data is corrupted with noise, which has a considerable influence on the characteristics of time series and by association on results of process control methods (Kamphuis et al., 2010). Wavelet filters are able to detect and exclude noise in data (Gencay et al., 2002; Ganesan et al., 2004; Pastell et al., 2009). Thus, in agricultural science wavelets were recently applied on data to study differences between animals (Pastell et al., 2009; Kruse et al., 2011). In industrial and chemical process control wavelet filtering is used successfully to enhance the fault diagnosis of statistical process control (SPC) methods (Lu et al., 2003). An important SPC tool is the cumulative sum (CUSUM) control chart, which can be used with a (reasonable) statistical

level of confidence to detect changes in production processes, including animal production systems (Lukas et al., 2009; de Vries and Reneau, 2010).

Thus the aim of this study was to explore wavelet filtering combined with CUSUM charts for early detection of mastitis and lameness in dairy cows.

## **2 Material and methods**

### **2.1 Data**

Data were recorded on the Karkendamm dairy research farm, University of Kiel, between January 2009 and October 2010. In total 46,427 cow days were accumulated from 237 Holstein Friesian cows. Because mastitis and lameness are diseases of the early stage of lactation (Green et al., 2002; Chuganda et al., 2006) only the first 200 days in milk (DIM) were used. The proportion of cows in their first lactation was 83%, 9% of the cows were in their second lactation, whereas 8% of the cows were in their third or a higher lactation. Milking took place in a rotary milking parlour manufactured by GEA Farm Technologies. Cows were milked twice daily. 90,794 milkings were recorded during the observation period. In addition, medical treatments of diseases were documented constantly by veterinarians and farm staff. In this study, milk electrical conductivity (MEC) and cow activity were used as indicators for the development of mastitis and lameness, respectively. One erroneous value of the MEC was excluded from the data set.

#### **2.1.1 Milk electrical conductivity**

MEC were measured using the Metatron P21 milk meter (GEA Farm Technologies) at every milking. This trait was originally measured in millisiemens (mS); however the on-farm parlour management software (GEA Farm Technologies) recalculated these values and reported them as reference units. The reference units were used in this investigation since the exact algorithm was not available for retransformation. Means of MEC of each cow and day were calculated to reduce intra-day variation. In total, 44,837 observations were included in the study. Daily MEC was 497.11 reference units on average (Table 1).

**Table 1.** Descriptive statistics of the data: number of observations (n), mean value ( $\bar{x}$ ), median, standard deviation (s), minimal (min) and maximal (max) values for the traits milk electrical conductivity (MEC), somatic cell count (SCC) and cow activity.

<b>Trait</b>	<b>n</b>	<b><math>\bar{x}</math></b>	<b>median</b>	<b>s</b>	<b>min</b>	<b>max</b>
<b>MEC</b> [reference units]	44,837	497.1	-	34.4	351.0	714.7
<b>SCC</b> [1,000/ml]	6,396	-	53.3	397.6	4.5	8,245.7
<b>Activity</b> [contacts/hour]	46,422	30.8	-	14.4	2.3	190.2

### 2.1.2 Cow activity

Activity was measured using pedometers (GEA Farm Technologies), which recorded activity in two-hour periods. Average daily activity rates were calculated to account for the diurnal rhythm. The average activity per day was 30.8 contacts per hour (Table 1).

## 2.2 Definition of disease

### 2.2.1 Mastitis

Cows were selected for veterinary treatment by the farm staff based on observable signs for mastitis. Because of the possibility of mastitis cases showing no visible signs, mastitis was classified on the basis of information on udder treatments as well as on the cows' somatic cell count (SCC) (Cavero et al., 2007; Kramer et al., 2009). SCC was measured weekly from pooled quarter milk samples taken from each cow. A total of 6,396 tests were carried out. Due to the skew distribution of the SCC, the median (53,290 cells/ml) instead of the average is given for this trait (Table 1). The European Union maximum bulk milk SCC threshold for saleable milk is set at 400,000 cells/ml. According to the "Deutsche Veterinärmedizinische Gesellschaft e.V." [German Veterinary Association] an inflammation of the mammary gland is present if the SCC exceeds the threshold of 100,000 cells/ml (DVG, 2002). A SCC measurement of more than 400,000 cells/ml or 100,000 cells/ml, respectively, was considered to be a case of mastitis (Cavero et al., 2007; Kramer et al., 2009). Consequently, three variants of mastitis definition were used in this study:

- 1) Treat: treatment performed without consideration of SCC
- 2) Treat 400: treatment performed and/or a SCC > 400,000 cells/ml
- 3) Treat 100: treatment performed and/or a SCC > 100,000 cells/ml

According to Caverio et al. (2007) the days in the dataset were classified as “days of health”, “days of disease” or “uncertain days”. In the case of treatment, the day of treatment as well as two days before were defined as “days of disease”. After the withdrawal period with no observation, cows were classified according to the SCC measurement. The day when the SCC was recorded, as well as two days before and two days after, were set to the status of the measured SCC classification. If two succeeding SCC measurements both exceeded the threshold of Treat 100 or Treat 400, respectively, all days between them were also defined as “days of disease”. If both thresholds were not exceeded, all days between the SCC measurements were classified as “days of health”. If the successive SCC measurements did not come to the same classification (healthy or disease), the day where the SCC was recorded, and two days after and two days before were defined according to this SCC-value. Existing days in the middle were set to uncertain days.

A disease block was defined as an uninterrupted sequence of “days of disease”. As the focus of this study was on early disease detection, only the days before a treatment were included in a disease block (Kramer et al., 2009). The first five days of each disease block were analysed in the case of mastitis defined by SCC (Caverio et al., 2007). The total amount of disease blocks as well as the percentage distribution of “days of health”, “days of disease” and uncertain days according to the three different mastitis definitions are shown in Table 2 a).

### **2.2.2 Lameness**

For veterinary treatment, lame cows were selected by the farm staff based on observable signs. Lameness was defined using disease blocks analogous to the mastitis definitions. The treatments served as the bases of these blocks (Kramer et al., 2009). The different definitions varied on the length of the disease blocks.

- 1) Treat 3: day of treatment including three days before the treatment
- 2) Treat 5: day of treatment including five days before the treatment

All medicated cows were observed by a veterinarian again one week after treatment. Thus, all days between treatment and another examination were set to “days of disease”. If the follow-up examination proved negative, cows were considered healthy. Otherwise, the disease block had to be lengthened. Only the days of a disease block before treatment occurred were analysed for early disease detection. Table 2 b) shows the total amount of disease blocks as well as the percentage distribution of “days of health”, “days of disease” and uncertain days according to the different lameness definitions.

**Table 2.** Amount of disease blocks found as well as percentage distribution of days of health, days of disease and uncertain days according to the different mastitis/lameness definitions considered.

a) Mastitis

Definition	Amount of blocks	Days of health [%]	Days of disease [%]	Uncertain [%]
Treat	61	99.5	0.5	-
Treat 400	179	93.0	4.1	2.8
Treat 100	548	68.8	25.4	5.7

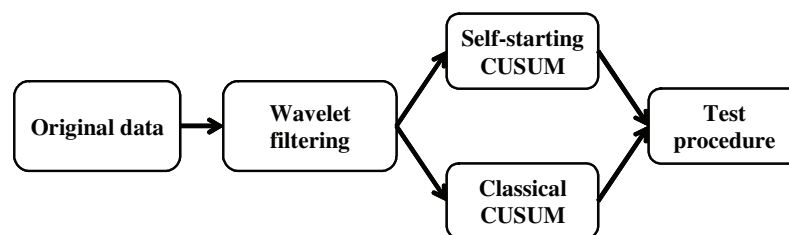
b) Lameness

Definition	Amount of blocks	Days of health [%]	Days of disease [%]	Uncertain [%]
Treat 3	178	93.4	6.6	-
Treat 5	178	92.7	7.3	-

## 2.3 Methods

Compared to industrial processes, data of livestock production time series show process dynamics or variability, like autocorrelations, which impede direct application of SPC methods (e.g. charts) (Montgomery, 2009; de Vries and Reneau, 2010; Mertens et al., 2011). Combining pre-processing methods with control charts are advised tools for permanent process improvements or reduction in variability (Montgomery, 2009; de Vries and Reneau, 2010; Mertens et al., 2011).

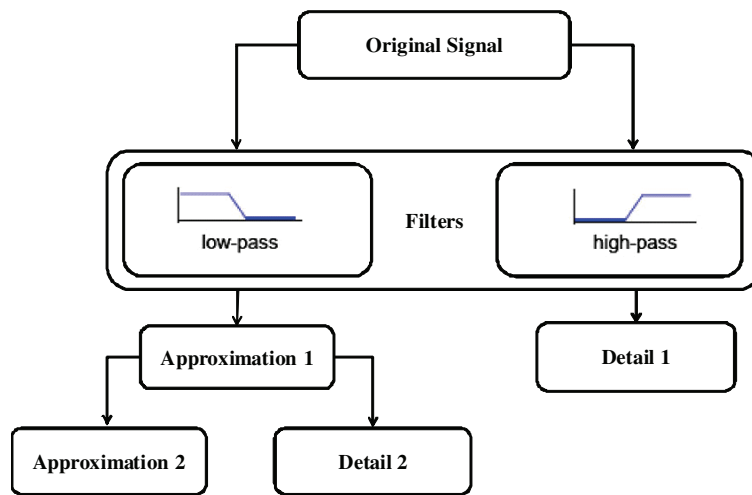
Figure 1 shows the general procedure of the study. At first, wavelet analysis was applied to the MEC and activity data for filtering, respectively. Then monitoring of the resulting values was performed either by a classic CUSUM chart or a self-starting CUSUM chart. Afterwards, the performances of mastitis as well as lameness detection of both charts were tested. All the steps of the general procedure were performed for each cow individually.



**Figure 1.** General procedure of the study.

### 2.3.1 Filtering using wavelet analysis

In wavelet theory, the wavelet transformation utilises a basic function, called the “mother” wavelet, that is stretched and shifted to capture time and frequency features of a time-dependent signal (serial data), such as MEC as well as pedometer activity (Daubechies, 1990; Lio, 2003). Wavelet filtering is based on discrete wavelet transform (DWT) (Sang et al., 2010). DWT is associated with low-pass and high-pass filters (Kara and Dirgenali, 2007). The goal of wavelet filtering is to transform a signal into coefficients to describe it without losing information (Kruse et al., 2011). Each decomposition (filtering) step of wavelet filtering is called level (Figure 2). For the first decomposition level, the coefficients are derived by separating the original signal (MEC and activity of each cow) into two complementary halves, i.e., approximation and detail coefficients (Figure 2).



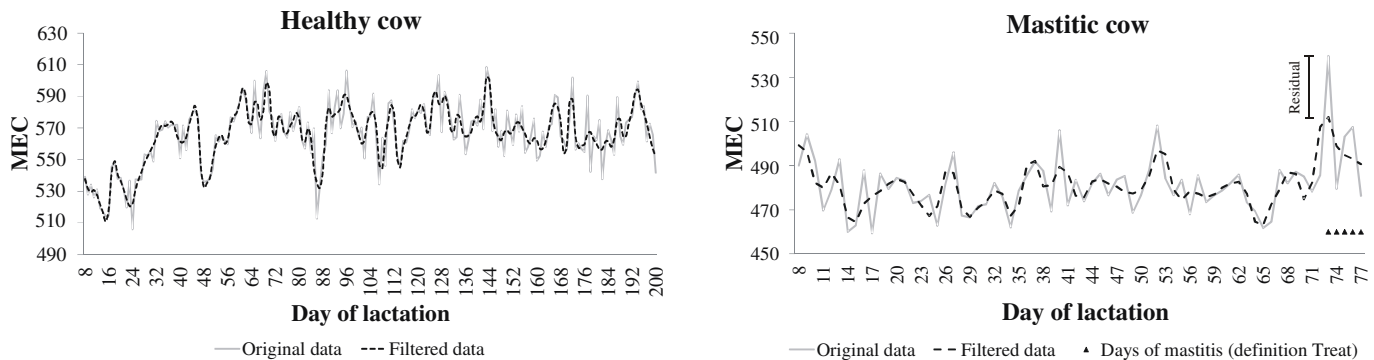
**Figure 2.** Wavelet decomposition levels and filtering process.

The approximation coefficients are the low frequency component, and the detail coefficients are the high-frequency component of the original signal. For most signals, the low-frequency content is the most important part since it stands for the underlying (real) signal or trend. The details imply transient events which are attributed to noise (Kara and Dirgenali, 2007). Thus the approximation coefficients are the basis for further filtering and pass through the same low-pass and high-pass filters. The coefficients at each decomposition level can further be adjusted, e. g. by specifying the thresholding rules for the low-pass and high-pass filters (Sang et al., 2010). Finally, the approximation coefficients can be used for reconstruction of a filtered signal at each decomposition level. The reconstructed but filtered MEC or activity



signal of each cow at a specific decomposition level can then be used for further analysis, such as CUSUM charts.

In short, wavelet filtering identifies which component of the signal contains noise, and then reconstructs the signal without those components (Figure 3).



**Figure 3.** Comparison of original and filtered values for the trait MEC (milk electrical conductivity) displaying data of healthy as well as ill cows and one example for residuals.

In the present study, MEC and activity data of each cow were individually decomposed using Daubechies 4<sup>th</sup> order wavelet (DB4). According to Gencay et al. (2002), the DB4 is one of the most flexible mother wavelets. Additionally, the suitability of the mother wavelet was tested by the maximal and average error of total reconstruction of the original signal. Thus, DB4 was chosen to be the best eligible basis for filtering the MEC and the activity signal of each cow. According to Gencay et al. (2002), a hard-thresholding rule and Heuristic sure thresholding were chosen to be best suitable for the data analysed and were applied to the coefficients. Furthermore, the second decomposition level was chosen to be the best level of filtering for both traits. In the case of MEC, residuals between the observed (original) value and the value of the filtered value were calculated (Figure 3). This was necessary to account for the underlying trend of naturally rising MEC during lactation, causing auto-correlations. Filtered activity data was not further processed. All calculations were computed using the MATLAB Wavelet Toolbox (MATLAB, 2010b). For more detailed information on wavelet analysis, refer to Daubechies (1990) and Gencay et al. (2002).

In the next step the residuals of the MEC and the filtered signals of the cow activity were to be monitored using CUSUM charts.

### 2.3.2 Classic CUSUM chart

Statistical process control (SPC) charts are well-known tools for quality control in industrial processes (Krieter et al., 2009). In general, a control chart consists of a centre line that represents the average value or the target value of the observed trait. Two other horizontal lines called the lower (LCL) and upper control limits (UCL) are also part of the chart. A data point outside the control limits is called an alert, indicating that the process is out-of-control. Corrective action is then required to restore or improve the process.

The classic CUSUM chart plots the cumulative sums of the deviations from the target value which is estimated from a sample dataset (prior data). The CUSUM control chart has a rather long memory due to the fact that it uses a non-weighted sum of all previous observations (Hawkins and Olwell, 1998). Since no prior data of each cow was available in the present study this classification method was used retrospectively.

The CUSUM method differentiates between upward and downward drifts, therefore a calculation of the upward ( $C_i^+$  or upper CUSUM) and downward cumulative sum ( $C_i^-$  or lower CUSUM) of the standardised observations ( $y_i$ ) was performed. They were computed as follows (Montgomery, 2009):

$$C_i^+ = \max[0, y_i - k + C_{i-1}^+]$$
$$C_i^- = \max[0, -k - y_i + C_{i-1}^-]$$

The CUSUM chart can be adjusted with the reference value  $k$ . Montgomery (2009) recommended that  $k$  should be chosen relative to the size of the shift that is to be detected. Low  $k$ -values make the chart more sensitive to changes (Hawkins and Olwell, 1998; Krieter et al., 2009). In the present study  $k$  was tested for the values of 0.1, 0.2 and 0.5 and then set to 0.2 for mastitis as well as for lameness detection at cow level.

To identify when the mean has shifted from the specified values, UCL and LCL are plotted on the charts. They are determined by the  $h$ -value (threshold value), also called the decision interval.

$$UCL = h$$
$$LCL = -h$$

The threshold value was varied from value 1 to 8. Results will be presented in later sections. For more details on classic CUSUM charts, see Hawkins and Olwell (1998) and Montgomery (2009).

### 2.3.3 Self-starting CUSUM chart

The classic CUSUM chart requires collection of a sample dataset with prior observations to calculate the target value. A self-starting CUSUM is a chart that can be plotted even when no prior data exist (Hawkins and Olwell, 1998). Self-starting methods update the parameter estimates (mean and variation) with each new observation. Both are updated by calculating a running mean and running variation. The standardisation of each observation, using the running mean and standard deviation of the preceding observations, gives a standardised variate ( $Z(i)$ ). This variate follows a Student's t-distribution (Hawkins and Olwell, 1998; Mertikas and Damianidis, 2007). However, estimating the mean and the standard deviation can be problematic because of the correlations between samples. If correlations exist, the distribution of the standardised variate is not exactly normal. Hence, the distribution of the standardised variate has to be transformed to become independent and follow the standard normal distribution. This is achieved by applying the following transformation (Hawkins and Olwell, 1998):

$$U(i) = \Phi^{-1}[G_{t-2}(Z(i))]$$

where  $\Phi^{-1}$  is the inverse normal cumulative distribution and  $G_{t-2}(\cdot)$  is the cumulative distribution function of the Student's t-distribution. After transformation, the quantities obtained ( $U(i)$ ) were shown to be independent and identically distributed as standard normal variates, with zero mean and variance equal to one (Hawkins and Olwell, 1998; Mertikas and Damianidis, 2007). The transformed quantities of each cow could then be handled as any data ( $y_i$ ) for a CUSUM chart and were applied and plotted according to the formulas of the classic CUSUM chart.

The reference value  $k$  was tested for the same values as in the classic CUSUM (0.1, 0.2, 0.5) and set to 0.2 in the case of mastitis and lameness detection. The threshold value for the UCL and LCL was varied in the aforementioned way (1 to 8).

For further information on self-starting CUSUM charts, refer to Hawkins and Olwell (1998).

## 2.4 Test procedure

The system described (wavelet filtering combined with CUSUM charts) provided an alert whenever a  $C_i^+$  on the MEC chart was above the UCL, since mastitis increases MEC (Lukas et al., 2009). In the case of lameness detection, an alert occurred if a  $C_i^-$  of the activity data was plotted outside the LCL, since lower cow activity indicates lameness. System performance was assessed by comparing these alerts with the actual occurrence of disease.

The concerning day of observation was classified as true positive (TP) if the threshold was exceeded on a day of disease, while an undetected day of disease was classified as false negative (FN). Each day in a healthy period was considered as 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.

Sensitivity represents the percentage of correctly detected days of disease of all days of disease:

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

For disease detection, it was not important for all days of a disease block to be recognised, but it was crucial for mastitis or lameness to be detected at all and early on. Therefore the block sensitivity was deemed considerably more important than sensitivity. For the block sensitivity, each disease block was considered a TP case if one or more alerts were given within the defined disease block and a FN case otherwise (Cavero et al., 2007; Kramer et al., 2009).

The specificity indicates the percentage of correctly found days of health 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 disease periods from all the days where an alarm was produced:

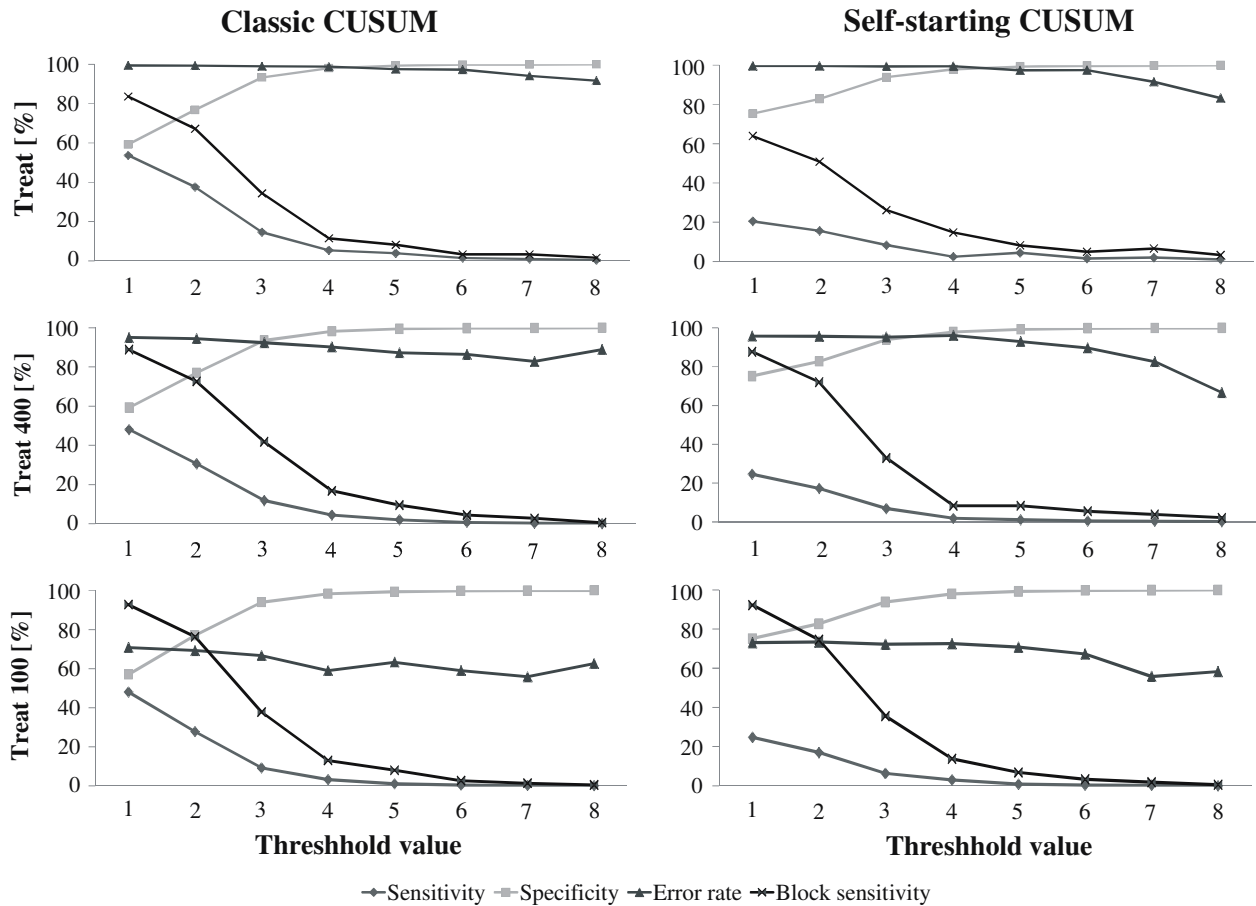
$$\text{error rate} = \frac{\text{false positive}}{\text{false positive} + \text{true positive}} \times 100$$

In addition, the number of false positive cows per day is given. This is a relatively important detail which stands for the effort of the mastitis and lameness monitoring system. All calculations were computed using SAS software (SAS, 2009).

### 3 Results

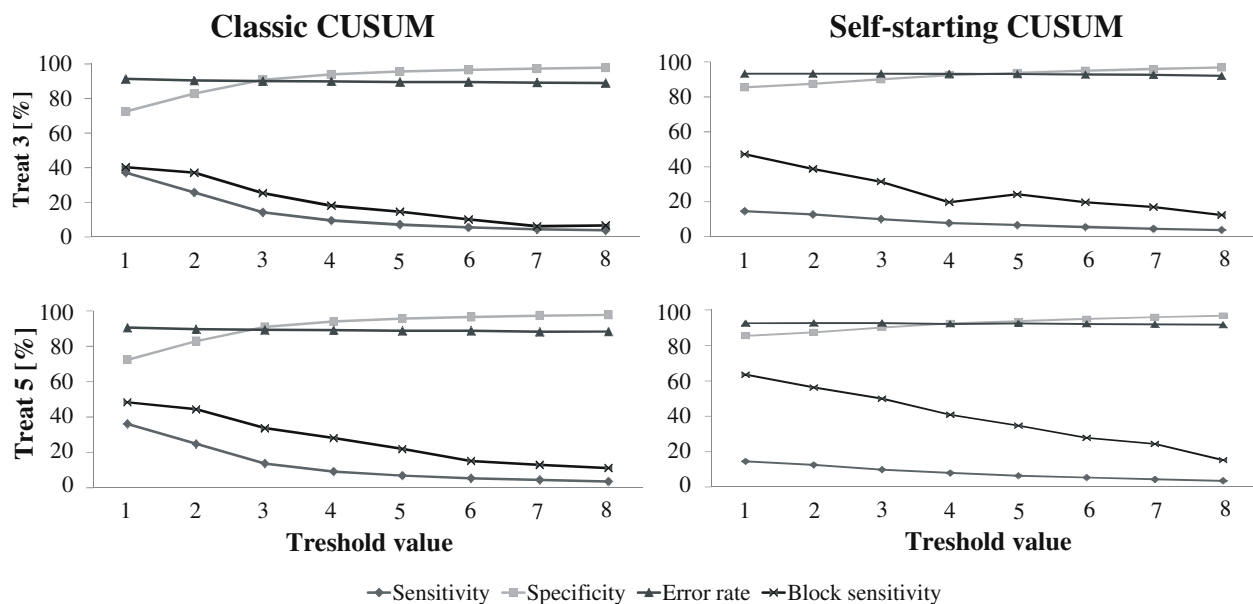
The results of both CUSUM charts and the three mastitis definitions are shown in Figure 4. Sensitivity, block sensitivity, specificity as well as the error rate of both charts at each mastitis definition and threshold value varied only slightly from each other. In general, (block) sensitivity decreased with increasing threshold value. As block sensitivity was considered more important than sensitivity, only block sensitivity is presented in more detail. The highest values for block sensitivity were reached at Treat 100 (92.7% for the classic CUSUM and 92.3% for the self-starting CUSUM). In contrast to (block) sensitivity, specificity increased with increasing threshold value.

The error rates generally decreased with increasing threshold values. The error rates of definitions Treat and Treat 400 for both charts did not differ much between each other. Treat 100 obtained the lowest error rates of all analyses (from 73.1 to 55.8%).



**Figure 4.** Comparison between the three mastitis definitions for the classic and self-starting CUSUM chart.

The results of lameness detection for the two lameness definitions are shown in Figure 5. As in the aforementioned mastitis detection analysis, (block) sensitivity and error rates decreased with increasing threshold value whereas specificity rose. The highest results for block sensitivity of lameness detection were reached at Treat 5 (48.3% for the classic CUSUM and 63.5% for the self-starting CUSUM). Thus, the self-starting CUSUM performed better in early lameness detection than the classic CUSUM chart. The specificities of the two lameness definitions within the different charts at a specific threshold value varied only slightly from each other. The specificities of the self-starting CUSUM (85.5 to 96.8%) were marginally higher at small threshold values than the specificities of the classic CUSUM (72.4 to 97.8%). Treat 5 obtained lower error rates compared to Treat 3, whereas the classic CUSUM (error rates of 90.6% to 88.2%) performed better than the self-starting CUSUM (error rates of 92.7% to 91.6%).



**Figure 5.** Comparison between the two lameness definitions for the classic and self-starting CUSUM chart.

Sensitivity and specificity are interdependent. Therefore, block sensitivity was set to be at least 70%, which is in line with Kramer et al. (2009). In addition to specificity and error rate at block sensitivity of 70% minimum, average true positive and false negative cows/day were also determined (Table 3). These two variables stand for the number of cows per day classified rightly or wrongly as diseased, respectively, and thus illustrates the farmers' effort with regard to mastitis or lameness monitoring.

**Table 3.** Results for both CUSUM charts depending on the disease definitions and requiring a block sensitivity of 70% minimum

a) Mastitis\*

Definition	Chart	Threshold value	Block sensitivity [%]	Specificity [%]	Error rate [%]	TP cows/day	FP cows/day
<b>Treat</b>	Classic	1	83.6	59.2	99.4	0.2	15.7
	Self-starting	1	63.9	75.3	99.6	0.1	16.8
<b>Treat 400</b>	Classic	2	72.6	77.0	94.4	0.9	15.0
	Self-starting	2	72.1	82.8	95.7	0.5	11.3
<b>Treat 100</b>	Classic	2	76.3	77.0	69.2	5.0	11.2
	Self-starting	2	74.5	82.7	73.4	3.0	8.4

b) Lameness\*\*

Definition	Chart	Threshold value	Block sensitivity [%]	Specificity [%]	Error rate [%]	TP cows/day	FP cows/day
<b>Treat 3</b>	Classic	1	40.4	72.5	91.3	1.9	11.2
	Self-starting	1	47.2	85.5	93.3	0.7	9.5
<b>Treat 5</b>	Classic	1	48.3	72.4	90.6	1.9	11.0
	Self-starting	1	63.5	85.5	92.6	0.7	9.4

\*Average herd size: 171 cows per day

\*\*Average herd size: 166 cows per day

The values of the classic charts at definition Treat reached block sensitivity above 70% (Table 3a)). However, high error rates of 99.4% and 16 FP cows per day (0.2 TP cows per day) were observed. The self-starting CUSUM for Treat did not attain the limit of 70%. The classical CUSUM for definition Treat 400 and Treat 100 performed better than the self-starting approach. Additionally, the error rates of the classic charts for Treat 400 and for Treat 100 were lower than for the self-starting charts. However, the amount of FP cows per day reached higher values on the classic chart. At Treat 400 and Treat 100 15 FP cows per day and 11 FP cows per day occurred, respectively, whereas the self-starting chart obtained values of 11 FP cows per day (Treat 400) and 8 FP cows per day (Treat 100).

In the case of lameness detection (Table 3b)) the highest block sensitivities were reached at a threshold value of 1. However, block sensitivity of the self-starting CUSUM at Treat 5 was

the only analysis close to the set block sensitivity limit of 70%, whereas all other block sensitivities were between 40.4% and 48.3%. In contrast to mastitis detection the self-starting CUSUM performed better than the classic CUSUM due to block sensitivity. Similar to mastitis detection the classic CUSUM showed a higher number of FP cows per day compared to the self-starting chart.

## **4 Discussion**

### **4.1 Classification of the results**

The aim of this study was the early detection of mastitis and lameness. Block sensitivities of more than 70%, specificities of around 75% and error rates between 70 to 99% were reached for mastitis detection. However, lameness detection showed block sensitivities of less than 50% and specificities of 80% while error rates were 90% or higher. For performance appraisal, the results have to be compared with other studies on health monitoring. In case of mastitis detection, e.g., Cavero et al. (2007) reached higher block sensitivities (>80%) combined with lower error rates (56 to 83%). However, these MEC values were measured on quarter level of each cow which gives better detection performance (Hogeveen et al., 2010). For lameness detection, Kramer et al. (2009) applied a multivariate fuzzy logic method. Although higher block sensitivities (>70%) were achieved the error rates were above the error rates of this univariate analysis.

Several other studies exist (e.g. de Mol et al., 2001; Pastell and Kujala, 2007; Lukas et al., 2009). However, the results of these investigations vary tremendously (18 to 100% sensitivity). One reason for this are the different characteristics between the studies, which make comparison difficult (Hogeveen and Ouweltjes, 2003; Cavero et al., 2007). Considerable differences, e.g., in the studies can be seen in the disease definitions. The SCC thresholds of mastitis used in this study are based on Cavero et al. (2007). Other investigations proposed thresholds of 150,000 to 200,000 cells/ml (Pyörälä, 2003; Windig et al., 2005). In the case of lameness, e.g., Pastell and Kujala (2007) used recorded treatments but also a locomotion scoring system to ensure lameness. However, gait scoring is subjective with a low inter- and intra-observer repeatability (Pastell and Kujala, 2007). Therefore, in the present study lameness definitions based on treatments were used, which is in line with Kramer et al. (2009).



Furthermore, the choice of the length of disease blocks has been widely varied (1 to 17 days) in past research on disease detection (de Mol et al., 1997; Hogeveen et al., 2010; Kamphuis et al., 2010). Block sensitivity increases if longer periods are considered (Kramer et al., 2009; Hogeveen et al., 2010). According to Hogeveen et al. (2010), an alert should be given for early disease detection before clinical signs are visible so that a treatment will have a higher efficiency and will reflect implementations of practice. Therefore, short time windows (two, three and five days) were used in the present study.

## **4.2 Wavelet filtering and CUSUM charts**

In the present study, wavelet filtering was used at cow level, which is recommended in several studies to account for individual reactions to diseases, leading to large intra-cow variability (Lukas et al., 2009; Brandt et al., 2010). Another advantage of wavelets is the application of filtering without accounting for other (maybe unknown) influences (e.g. stage of lactation, seasonal influences, lactation number) on the data such as in (e.g. mixed) models (Chuganda et al., 2006; Lukas et al., 2009). Hence, wavelet filtering was able to adapt flexibly to the data of each cow, but there is still a need for adjustments by the scientist (Gencay et al., 2002; Lio, 2003; Sang et al., 2010). The choice of DB4 as the best suitable mother wavelet was based on the literature and tested using the maximal as well as the average error of total reconstruction of the original signal. More problematic is the choice of the best decomposition level. There is the possibility to use the white noise testing method. This method though performs inaccurately and unreliably in many practical situations (Sang et al., 2010). Thus, the decomposition level still has to be chosen based on the experience of the scientist (Gencay et al., 2002).

Additionally, wavelet filtering is a signal processing technique. Generally, in signal processing, shorter sampling intervals do exist than in agricultural science (e. g. milking twice daily). If the sampling rate is not high enough to sample the signal correctly, then a phenomenon called aliasing can occur (Jun-Zeh et al., 2005). Hence, results show trends which would be different if more data samples had been available in a shorter time. In the present study, naturally rising MEC during lactation (Lukas et al., 2009) as well as relatively homogeneous cow activity was displayed after filtering so it is most likely that the aliasing effect did not affect the results.

CUSUM in general is used to detect small changes in processes (Montgomery, 2009). Therefore, studies in on-farm disease detection have used CUSUM charts to identify the early

emergence of health disorders in farm animals (Quimby et al., 2001; Madsen et al., 2005; Mertens et al., 2011). Like wavelet filtering, CUSUM charts can be used for individual cows so that the combined monitoring system (wavelets and CUSUMs) still works at cow level.

One disadvantage of the classic CUSUM is the need for the mean and variance of each cow to describe the individual process performance beforehand (Montgomery, 2009). Test data sets of each cow (82% first lactating cows) were not available so that this method could only be used retrospectively. To overcome the retrospective consideration, self-starting CUSUM charts were used.

However, increased variation at the onset of charting reduces the sensitivity of the charts significantly (Hawkins and Olwell, 1998). Mastitis in particular is a disease of early lactation (DVG, 2002) so that high values of MEC have a great impact on the calculated running mean and standard deviation. This could be one reason for the better performance of the classic CUSUM chart compared to the self-starting chart in the case of mastitis detection.

### **4.3 Traits**

The usage of MEC and cow activity, respectively, as the only indicators for mastitis and lameness is arguable. Mastitis and lameness are complex multifactorial diseases (Brandt et al., 2010). Consequently, increased electrical conductivity or low cow activity might be associated with problems other than mastitis or lameness (Hogeveen and Ouweltjes, 2003; Chuganda et al., 2006). Therefore, MEC and cow activity alone are not sufficient to detect abnormal milk and lameness automatically and could be one reason for the high error rates. Furthermore, new sensor developments, such as infrared spectroscopy and biosensors, inclusion of other traits (e.g. stage of lactation, milk yield, concentrates intake) or considerations of prior diseases might generate additional and more accurate traits which help to enhance monitoring the health status of dairy cows in the future (Gröhn et al., 2004; Brandt et al., 2010; Hogeveen et al., 2010).

## 5 Conclusion

Overall, wavelet filtering was applicable on MEC and activity data. Wavelets were able to identify the underlying real process or trends of a signal and enable analyses of time series without such trends. It seems to be an aid for individual disease detection in dairy cows but further analyses are needed. Although relatively high block sensitivities of about 70% were attained in both charts and nearly every variant of the disease definitions, the corresponding error rates and amounts of FP cows per day were too high. The usage of detection methods apart from CUSUM charts might produce better results which make wavelet filtering applicable in practice. MEC and cow activity on their own do not seem sensible to detect mastitis or lameness reliably. Results could probably be enhanced if more traits, e.g. stage of lactation, milk yield, concentrates intake and prior knowledge of infections of each cow, were included in a multivariate analysis.

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# **CHAPTER TWO**

## **Principal component analysis for the early detection of mastitis and lameness in dairy cattle**

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## Abstract

This investigation analysed the applicability of principal component analysis (PCA), a latent variable method, for the early detection of mastitis and lameness. Data used was recorded on the Karkendamm dairy research farm between August 2008 and December 2010. For mastitis and lameness detection, data of 338 and 315 cows in their first 200 days in milk were analysed, respectively. Mastitis as well as lameness was specified according to veterinary treatments. Diseases were defined as disease blocks. The different definitions used (two for mastitis, three for lameness) varied solely in the sequence length of the blocks. Only the days before the treatment were included in the blocks. Milk electrical conductivity, milk yield and feeding patterns (feed intake, number of feeding visits and feeding time) were used for recognition of mastitis. Pedometer activity and feeding patterns were utilised for lameness detection. To develop and verify the PCA model, the mastitis and the lameness datasets were divided into training and test datasets. PCA extracted uncorrelated principle components (PC) by linear transformations of the original variables so that the first few PCs captured most of the variations in the original dataset. For process monitoring and fault detection, these resulting PCs were applied to the Hotelling's  $T^2$  chart and to the residual control chart. The results show that block sensitivity of mastitis detection ranged from 77.4% to 83.3%, whilst specificity was around 76.7%. The error rates were around 98.9%. For lameness detection, the block sensitivity ranged from 73.8% to 87.8% while the obtained specificities were between 54.8% and 61.9%. The error rates varied from 87.8% to 89.2%. In conclusion, PCA seems not yet transferable into practical usage. Such results could probably be improved if different traits and more informative sensor data are included in the analysis.

Keywords: mastitis detection, lameness detection, principal component analysis, multivariate control charts



# **1 Introduction**

Mastitis and lameness still remain the most frequent and costly diseases in the dairy industry in terms of economics and animal welfare (Kramer et al., 2009). Early detection and intervention of mastitis and lameness reduces losses in milk yield, veterinary fees and losses in milk quality, and increases the cure rate of the infected animals (Milner et al., 1997). With growing herd size and the introduction of robotic milking the classical detection method of visual observations has become more difficult and time-consuming. Thus, there is a need to support the farmer's observations by applying improved and automated detection of diseases (de Mol et al., 1997). Automated detection is possible using sensor measurements and information from a Management Information System (MIS). Information from the MIS is useful for the judgement of the causes of aberrations. Much research has been done on the development of sensors and appropriate models to detect diseases. For mastitis detection, milk parameters (such as milk yield, milk electrical conductivity) have been used (Cavero et al., 2008; Lukas et al., 2009). For lameness detection, on the other hand, the activity of cows has been used (Kramer et al., 2009). Recently, feed intake and its corresponding behaviour have been reported to be linked to a cow's health status (Gonzalez et al., 2008; Lukas et al., 2008). However, only single variables are often looked at in detection models or different variables are considered successively. A disease may nevertheless influence milk yield, cow activity and feed intake. Therefore, examining one of these variables at a time as though they were independent, makes interpretation and diagnosis difficult (Kourti and MacGregor, 1995). This suggests that the results of a detection model may be improved by combining all of the variables and transforming them into useful information for the herdsman (de Mol et al., 1997; Cavero et al., 2008; Kramer et al., 2009).

Several studies have attempted to develop a multivariate scheme which would allow early disease detection based on cow monitoring. For mastitis detection, e.g., Kamphuis et al. (2010) used decision trees. Cavero et al. (2008) applied neural networks to monitor udder health whereas Pastell and Kujala (2007) used this method for lameness detection. Additionally, Kramer et al. (2009) exerted fuzzy logic for mastitis as well as lameness detection. Although high levels of sensitivities and specificities were reported, few of these models have been implemented in practical monitoring due to too high error rates. Additionally, a large number of false positive alerts provided by management software hinder their application in practice (Hogeveen et al., 2010). Thus, there is a strong need for improvement of the performance of analytical detection models so that they do not remain the missing link in automated disease detection.

Latent structure methods are used effectively for fault detection in chemical and industrial process control (Kourti, 2002; Choi et al., 2005). One approach that has proved particularly powerful is the use of principal component analysis (PCA), combined with Hotelling's  $T^2$  and residual monitoring charts since it allows an extension of the principles of univariate statistical process monitoring (e.g. control charts) to monitor of multivariate processes (Choi et al., 2005; Kourti, 2006). PCA is able to simultaneously divide all the data information into significant patterns, such as tendencies or directions, and into uncertainties, e. g. noises or outliers. Thus, PCA reduces the problem of discriminating between the process variables and of identifying new sets of variables which characterise all of the prior information (Burstyn, 2004).

Therefore, the aim of this study was to explore PCA combined with control charts ( $T^2$  and residual charts) for the early detection of mastitis and lameness in dairy cows.

## **2 Materials and Methods**

### **2.1 Data**

Data used was recorded on the Karkendamm dairy research farm between August 2008 and December 2010. For mastitis and lameness detection, about 66,000 cow-days from 338 and 315 cows in their first 200 days in milk (DIM) were analysed, respectively. Milk electrical conductivity, milk yield and feeding patterns (feed intake, number of feeding visits and feeding time) were used for recognition of mastitis. Pedometer activity and feeding patterns were utilised for lameness detection. Milking took place in a rotary milking parlour manufactured by GEA Farm Technologies. Cows were milked twice daily. Milk yield (MY) and milk electrical conductivity (MEC) were measured using the Metatron P21 milk meter (GEA Farm Technologies) at every milking. Activity was measured using pedometers (GEA Farm Technologies), which recorded activity in two-hour periods. Average activity rates per day were calculated to account for the diurnal rhythm. Furthermore, high pedometer activity due to documented and progesterone-measured oestrus events was excluded from the dataset. The feeding trough was developed and installed by the Institute of Animal Breeding and Husbandry, University of Kiel. Each visit to the feeding troughs was recorded and the amounts of consumed feed (forage) were accumulated to daily intakes. Extreme values (mainly for the trait feed intake) which deviated by more than  $\pm 4$  standard deviations were excluded from the dataset.

Medical treatments of diseases were documented constantly by veterinarians and farm staff. Different categories for mastitis (e.g. *Staphylococcus aureus* or *Escherichia coli* mastitis) and for lameness (e. g. digital dermatitis or sole ulcer) were identified. Due to the low number of diseased cows within these categories, the categories were combined to form cases of mastitis and lameness, respectively. These cases were defined as the target characteristic to be distinguished from the healthy observation in the data.

The application of principal component analysis (PCA) necessitates the division of the mastitis and lameness dataset, respectively, into training (randomly selected healthy cows during their 200 DIM) and test datasets (healthy and ill cows). For a sufficiently large training dataset, 100 cows without any cases of mastitis or lameness during their first 200 DIM were randomly selected, respectively (Aapo Hyvärinen, personal communication, October 15, 2011) (Table 1). Thus, 238 cows for the test dataset of mastitis were used, incorporating 138 cows without any mastitis treatment during their first 200 DIM as well as 100 cows which were treated for mastitis during this observation period. In case of the test dataset for lameness detection, 73 healthy and 142 infected cows were used. Descriptive statistical information on the traits for the training and test datasets with regard to their use in mastitis or lameness detection are also shown in Table 1.

**Table 1:** Means of the analysed traits for the training and test datasets of lameness and mastitis detection (standard deviations in parenthesis).

Trait	Mastitis		Lameness	
	Training	Test	Training	Test
<b>Number of cows</b>				
all	100	238	100	215
healthy	100	138	100	73
ill	-	100	-	142
<b>MY<sup>1</sup></b> (kg/milking)	18.2 (3.6)	18.4 (3.8)	18.0 (3.7)	18.0 (3.7)
<b>MEC<sup>2</sup></b> (reference units/milking)	490.3 (32.0)	497.5 (34.9)	493.5 (35.6)	494.7 (36.0)
<b>Daily activity</b> (contacts/h)	32.1 (14.2)	32.8 (14.7)	32.7 (8.9)	30.9 (10.2)
<b>Feed intake</b> (kg/day)	39.9 (11.2)	39.5 (11.1)	40.6 (11.1)	39.0 (11.1)
<b>Number of feeding visits per day</b>	45.8 (13.7)	45.8 (14.1)	47.6 (14.0)	45.1 (13.8)
<b>Feeding time</b> (min/day)	177.3 (50.3)	176.3 (52.3)	181.0 (49.0)	176.5 (52.3)

<sup>1</sup>MY=Milk yield

<sup>2</sup>MEC = milk electrical conductivity

## **2.2 Disease definition**

Diseases were defined as disease blocks, i.e. an uninterrupted sequence of “days of disease” (Cavero et al., 2008; Kramer et al., 2009). The treatments served as a basis for these disease blocks and the different definitions varied solely on the sequence length of the blocks. As the focus of this study was on early disease detection, only the days before a treatment were included in a disease block (Kramer et al., 2009). If at least one alarm was generated by the monitoring system within the block, it was considered as detected.

### **2.2.1 Mastitis definition**

Cows were selected for veterinary treatment by the farm staff based on observable signs of mastitis infection. Two variants of mastitis definition were used in this study:

Mastitis+3: treatment performed including three days before the treatment

Mastitis+4: treatment performed including four days before the treatment

The days in the dataset were classified as “days of health” or “days of disease” according to Cavero et al. (2007). The day of treatment as well as three or four days before was defined as “days of disease”, respectively. To give consideration to the withdrawal period without any observation, at least seven days after the last treatment of a mastitis case were not utilised for the analysis. After this period, cows were considered to be healthy. The data contained 115 disease blocks.

### **2.2.2. Lameness definition**

For veterinary treatment, lame cows were also selected by the farm staff based on observable signs. Lameness was defined using disease blocks analogous to the mastitis definitions. The different definitions varied in the length of the disease blocks.

Lame+3: day of treatment including three days before the treatment

Lame+5: day of treatment including five days before the treatment

Lame+7: day of treatment including seven days before the treatment

All medicated cows were again observed by a veterinarian one week after treatment. Thus, all days between treatment and another examination were set to “days of disease”. If the follow-up examination proved negative, cows were considered healthy. Otherwise, the lameness block had to be lengthened until the infected animals are considered to be healthy. For the

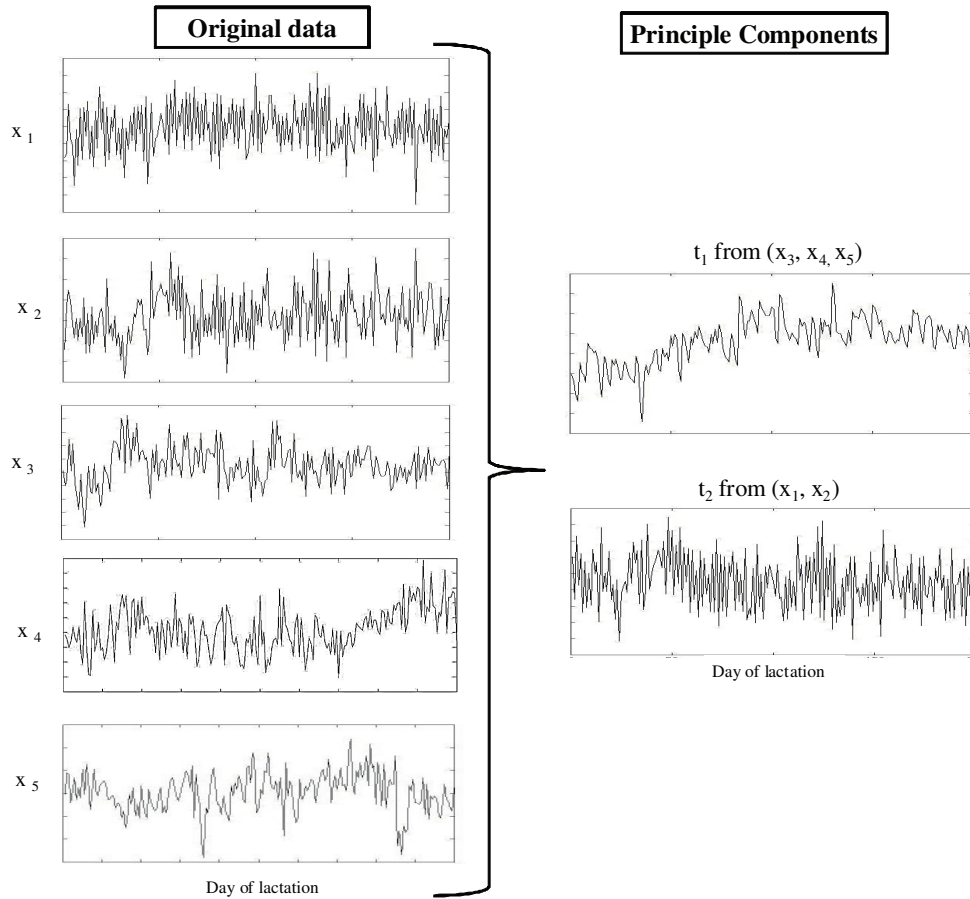
analysis, solely the days before the first treatment were used. The data contained 210 disease blocks.

## **2.3. Methods**

### **2.3.1 Methodology of Principal Component Analysis**

Principal component analysis (PCA) is a multivariate technique, also referred to as a latent variable method or projection method (Abdi and Williams, 2010). Its goal is to extract the important information from a number of possibly correlated variables and to represent it as a set of new uncorrelated and fewer variables, called principal components (PC). The first PC accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

In theory, PCA considers a mean-centred and scaled dataset,  $X$ , with  $n$  observations on  $k$  variables (mastitis dataset:  $k=5$ ; lameness dataset:  $k=4$ ). The first PC ( $t_1$ ) showing maximum variance is defined as the linear combination  $t_1 = Xp_1$ . The second PC ( $t_2 = Xp_2$ ) has the next greatest variance and subject to the condition that it is uncorrelated with  $t_1$  (Kourti, 2002; Montgomery, 2009). Up to  $k$  PCs are similarly defined. The  $p_i$ 's are constants to be determined (principle component loadings) using eigenvectors of the covariance matrix of  $X$ . Figure 1 gives a simplified schematic interpretation of the method using the mastitis detection variables as an example and by means of one cow.



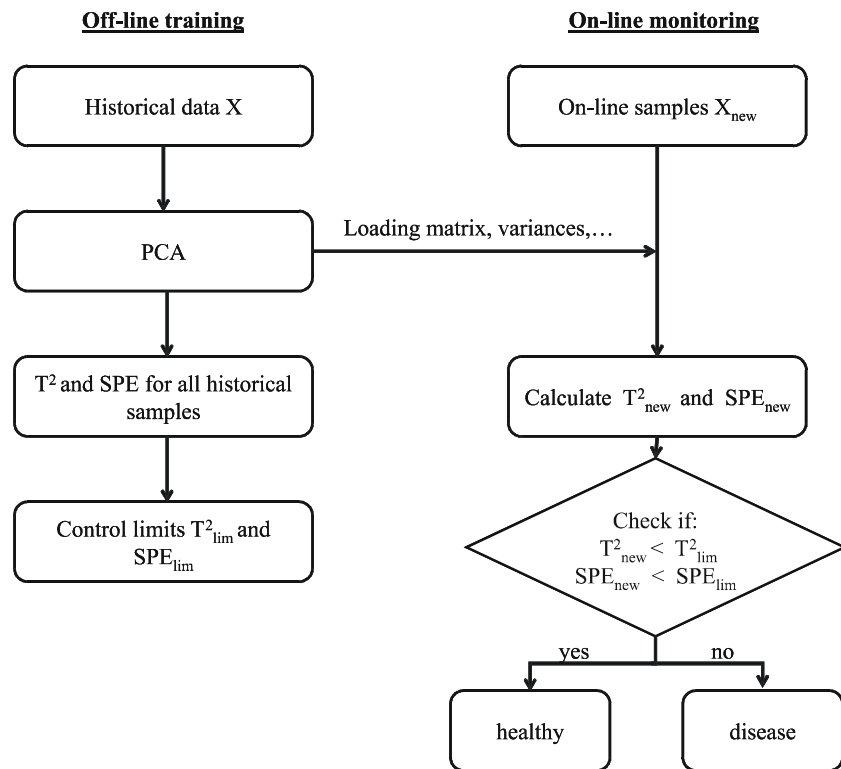
**Figure 1:** PCA and dimensionality reduction, based exemplarily on the input variables for mastitis detection and on one cow. The principal components  $t_1$  and  $t_2$  use the correlation of five variables ( $x_1$ =milk yield,  $x_2$  = milk electrical conductivity,  $x_3$  = feed intake,  $x_4$  = time at the through,  $x_5$  = number of visits) and break the process into two uncorrelated events.

There are five variables in a continuous process ( $x_1$ =MY,  $x_2$ = MEC,  $x_3$ = feed intake,  $x_4$  = time at the through,  $x_5$ = number of visits). Variables  $x_3$ ,  $x_4$  and  $x_5$  are more correlated with each other, while variable  $x_1$  is more correlated with  $x_2$ . New variables are calculated using PCA. The first principal component  $t_1$  is a weighted average of  $x_3$ ,  $x_4$  and  $x_5$ , while the second component,  $t_2$ , is a weighted average of  $x_1$  and  $x_2$ .

There are no firm guidelines on how many principle components have to be retained (Montgomery, 2009). Sufficient components to explain a reasonable proportion of the total process variability (70% and higher) should be taken into account (Choi et al., 2005; Kourti et al., 2009). The first two PCs incorporated 79% of the variance for mastitis detection, whereas  $t_1$  and  $t_2$  explained 87% of the process variance for lameness monitoring. Thus, both processes were reduced to the first two PCs.

### 2.3.2 Process monitoring and on-line disease detection

The procedure described above is used to establish a PCA model based on historical data collected when only common cause variation was present (training dataset, healthy cows only) (MacGregor et al., 2005) (Figure 2., off-line training). Any periods containing variations arising from special events (e.g. disease) which one would like to detect in the future are theoretically omitted at this stage (Kourti, 2002). New multivariate observations ( $X_{new}$ ) can then be referenced against this ‘in-control’ model using the PCA loading vectors to obtain their new PCs ( $t_{i,new} = p_i X_{new}$ ) (Figure 2, on-line monitoring).



**Figure 2:** Procedure of the model construction and on-line monitoring.

Two complementary multivariate control charts are required for process monitoring using projection methods such as PCA (MacGregor et al., 2005; Kourti, 2006) (Figure 2). The first is the Hotelling’s  $T^2$  chart on the remaining PCs.

$$T_{i,new}^2 = \sum_{i=1}^a \frac{t_{i,new}^2}{s_{t_i}^2}$$

$t_{i,new}$  incorporates the new PCs from the PCA model whereas  $s_{t_i}$  is the variance of the corresponding estimated latent variables ( $t_i$ ) in the training dataset. This chart will check

whether new observations of the measured variables are within the limits (Figure 2) determined by the training data. These upper control limits (UCL, threshold value) are obtained using the F-distribution of the training data (MacGregor and Kourti, 1995).

$$T_{lim}^2 = \frac{a(n-1)(n+1)}{n(n-a)} F_{\alpha}(a, n-a; \alpha)$$

where  $F_{\alpha}(a, n - a)$  is the upper  $100\alpha\%$  critical point of the F-distribution with  $a$  and  $n - a$  degrees of freedom ( $a$ : number of PCs;  $n$ : sample number) with level of significance  $\alpha$  (MacGregor and Kourti, 1995). It was mentioned above that the principal components explain the main variability of the system. The variability which cannot be explained forms the residuals (squared prediction error, SPE). This residual variability is also monitored and a control limit for typical operation is established. By monitoring the residuals, it is tested whether the unexplained disturbances of the system remain similar to the ones observed when the model was derived. If a totally new type of special events occurs which was not present in the training data, then new PCs will appear and the new observations  $x_{i,new}$  will not be in the defined range of the PCA model (Figure 2). The SPE can be computed by

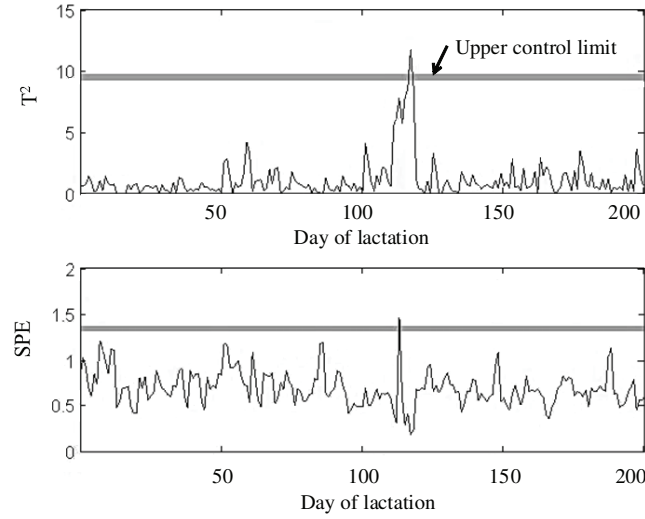
$$SPE_{i,new} = \sum_{i=1}^k (x_{i,new} - \hat{x}_{i,new})^2$$

where  $\hat{x}_{i,new} = p_i t_{i,new}$ . The upper control limit for the SPE chart ( $SPE_{lim}$ ) is given by

$$SPE_{lim} = (s/2m)\chi_{\alpha}^2(2m^2/s)$$

where  $m$  and  $s$  are the sample mean and variance of the SPE values from the training data (Zhang et al., 2010). In this study, the critical point of the F- and  $\chi^2$ -distribution in both ( $T^2$  and SPE) UCL's was varied from 99.9 to 50% in order to observe the properties of the monitoring system. The last step of this monitoring system is to check whether  $T_{i,new}^2$  and  $SPE_{i,new}$  is within the limits of the  $T^2$  or SPE chart (healthy) or not (disease) (Figure 2). Figure 3 shows an example of a  $T^2$  and an SPE control chart on one cow during its 200 DIM. All these calculations were computed using Matlab software (Matlab, 2010a).





**Figure 3:** Example of a Hotelling's  $T^2$  ( $T^2$ ) and SPE (standard prediction error) control chart on one cow. The measurements collected from the process variables at each instant in real time are translated into one point on the  $T^2$  chart and one point on the SPE chart.

## 2.4 Test procedure

The system described (PCA combined with  $T^2$  and residual charts) provided an alert whenever values above the UCL of the charts occurred (Figure 3). System performance was assessed by comparing these alerts with the actual occurrence of disease.

The corresponding day of observation was classified as true positive (TP) if the threshold was exceeded on a day of disease, while an undetected day of disease was classified as false negative (FN). Each day in a healthy period was considered as a true negative case (TN) if no alerts were generated, and as 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. Sensitivity represents the percentage of correctly detected days of disease of all days of disease:

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

For disease detection, it was not important for all days of a disease block to be recognised, but it was crucial for mastitis or lameness to be detected at all and early on. Therefore, the block sensitivity was deemed considerably more important than sensitivity. For the block sensitivity, each disease block was considered a TP case if one or more alerts were given within the defined disease block and an FN case otherwise (Cavero et al., 2007; Kramer et al., 2009).

The specificity indicates the percentage of correctly found days of health 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 disease periods from all the days where an alarm was produced:

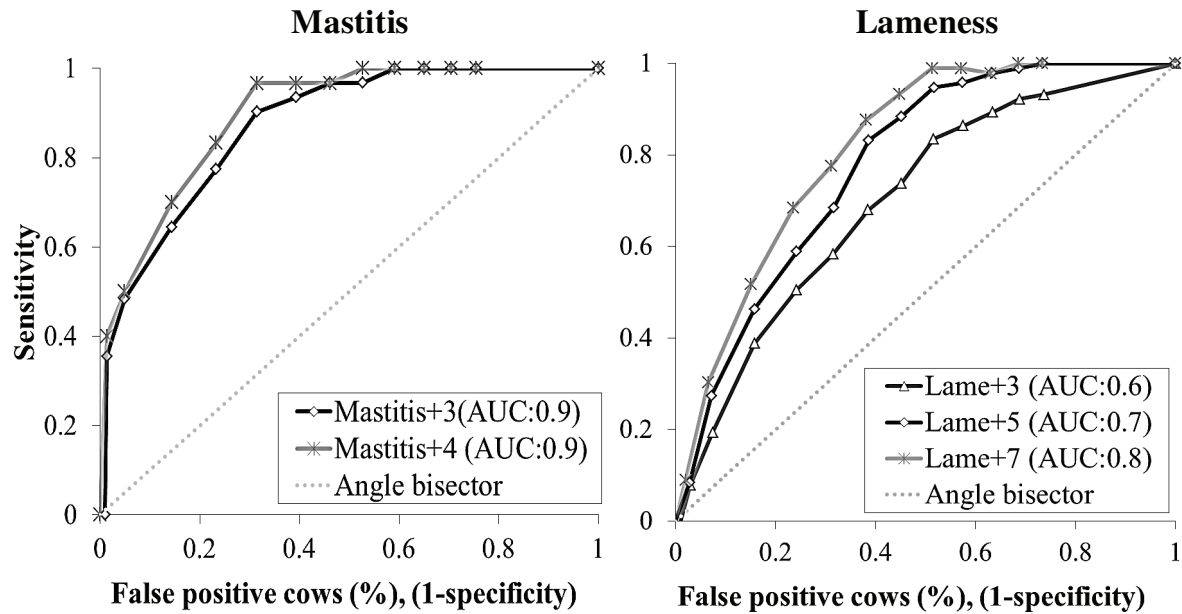
$$\text{error rate} = \frac{\text{false positive}}{\text{false positive} + \text{true positive}} \times 100$$

In addition, the number of true positive (TP) as well as false positive (FP) cows per day is given. TP and FP cows per day signify the average number of rightly and wrongly diseased-registered cows per day, respectively.

One statistical tool for assessing the accuracy of diagnostic predictions, i.e. the ability to differentiate between healthy and ill correctly, is ROC (receiver operating characteristic) curves combined with the area under the curve (AUC) as an important index. The calculated sensitivities and specificities can be plotted with respect to cut-off levels. In such plots or ROC curves, the false positive fraction (1 - specificity) is at the X-axis while the sensitivities form the Y-axis. It is often useful to enhance ROC curve plots with the inclusion of an angle bisector (Figure 4). The steeper the curve (more distant from the angle bisector), the greater the accuracy is. Besides the visual information on accuracy which a ROC curve creates, it is desirable to produce quantitative summary measures such as the area under the ROC curve (AUC). The closer AUC moves to 0.5, the poorer the test performs. The closer AUC lies to 1, the better the test is able to differentiate between healthy and ill.

### 3 Results

PCA combined with the control charts for mastitis detection mentioned showed similar ROC curves for the mastitis definitions considered whereas the definitions used for lameness detection produced a different accuracy (Figure 4). Overall, ROC curves of mastitis detection provided higher accuracies than for lameness detection. The AUC values also given in Figure 4 (parenthesis) show that for mastitis detection the values are close to 1 (0.9) whereas for lameness detection the AUC values ranged between 0.6 and 0.8.



**Figure 4:** ROC (receiver operating characteristic) curves for mastitis and lameness detection depending on the definitions used. The respective AUC (area under the curve) is stated in parenthesis below the graphs.

The optimal threshold value can be chosen depending on the use of the method determining whether a high sensitivity or a high specificity is desired. According to Hogeveen et al. (2010), the sensitivity of AMS should be at least 80%, whereas for milking parlours, such as the one in Karkendamm, the sensitivity is lower. Thus, the block sensitivity was set to be at least 70%, which is in line with Kramer et al. (2009). Table 2 shows the results of mastitis (2a) and lameness detection (2b) depending on the disease definitions and requiring a block sensitivity of least 70%. In addition to (block) sensitivity, specificity and error rate, the average true positive and false negative cows per day were also determined. These two variables indicated the number of cows per day classified rightly or wrongly as diseased, respectively, and thus illustrates the monitoring systems' effort with regard to mastitis or lameness monitoring.

Mastitis+3 reached a block sensitivity of 77.4% whereas the block sensitivity of Mastitis+4 was 83.3% (Table 2a). The specificity of both mastitis definitions were at 76.7%. However, high error rates of nearly 99% were observed. The number of FP cows per day for both mastitis definitions were 15.2 (Mastitis+3) and 15 (Mastitis+4) cows at an average herd size of 56 cows per day.

**Table 2:** Results of mastitis (a) and lameness detection (b) depending on the disease definitions and requiring a block sensitivity of least 70%.

a) Mastitis\*

	<b>Threshold value</b>	<b>Block sensitivity</b>	<b>Specificity</b>	<b>Error rate</b>	<b>TP cows/day</b>	<b>FP cows/day</b>
Mastitis+3	90	77.4	76.7	98.9	0.2	15.2
Mastitis+4	90	83.3	76.7	98.8	0.2	15.0

b) Lameness\*\*

	<b>Threshold value</b>	<b>Block sensitivity</b>	<b>Specificity</b>	<b>Error rate</b>	<b>TP cows/day</b>	<b>FP cows/day</b>
Lame+3	75	73.8	54.8	89.2	1.3	12.3
Lame+5	80	83.2	61.4	88.5	1.3	9.9
Lame+7	80	87.8	61.9	87.8	1.3	9.3

\*Average herd size: 56 cows per day

\*\*Average herd size: 47 cows per day

For lameness determination (Table 2b), Lame+7 showed highest block sensitivity (87.8%) compared to Lame+3 (73.8%) and Lame+5 (83.2%). While the specificities between the second and third lameness definitions varied slightly around 61%, Lame+3 reached a specificity value of 54.8%. Poorer results for Lame+3 were also obtained for the error rate (89.2%) compared to Lame+5 (88.5%) and Lame+7 (87.8%).

Showing 12.3 FP cows per day, the first lameness definition compared unfavourably to Lame+5 (9.9 FP cows per day) and Lame+7 (9.3 FP cows per day) in relation to an average herd size of 47 cows per day.

## 4 Discussion

The ROC curves and the AUC values show that for both diseases the monitoring system (PCA and charts) used were able to distinguish between ill and healthy animals, especially for mastitis detection (AUC value 0.9).

With regard to (block) sensitivity above 70%, the detection performance of the monitoring system of both diseases was acceptable. Specificities, however, were only around 70% and below, especially for lameness detection. Additionally, the error rates were too high at about 90%. The error rate is mainly affected by the number of FP alerts, which was high in the present study. Around 20% of the cows of the average herd size (mastitis n=56; lameness

n=47) were wrongly classified as ill per day for both diseases. This means more workload for the farmer accompanied by a loss of confidence in the monitoring system. Such unfavourable results can be caused by several reasons.

First, the disease definition is very important and subsequently influences classification results. In this study, an animal was considered to be ill if a treatment occurred. These treatments were carried out by a qualified veterinarian and can therefore be considered reliable.

According to Hogeveen et al. (2010), an alert should be given before clinical signs are visible so that a treatment has a greater efficiency and reflects the implementations of practice. Therefore, disease blocks were analysed before treatment occurred. Bareille et al. (2003) stated that mastitis effects milk production at three days whereas feed intake is disturbed by mastitis at around four days before visual onset of this disease. Thus, three- and four-day periods before clinical signs were chosen for mastitis detection. Up to five days have been reported to identify lameness (e.g. Bareille et al. 2003). Furthermore, Gonzalez et al. (2008) showed that lame cows change their feeding behaviour in a 30-day period before disease occurs. Hence, three-, five- and seven-day periods before clinical outbreak, i.e. an occurrence of the first treatment, were used for lameness detection.

However, the choice of the length of the disease blocks has varied widely (1 to 17 days) in past research on disease detection (de Mol et al. 1997; Hogeveen et al. 2010; Kamphuis et al. 2010). For instance, de Mol and Woldt (2001) indicated seven days before mastitis treatment occurred. Caverio et al. (2008) utilised disease blocks of five days (day of treatment plus two days prior and after treatment) for mastitis detection. In general, block sensitivity increases if longer periods are considered. In consequence, a comparison of model performance with other studies is difficult.

Another reason for the unfavourably high number of FP cows per day might be the fact that there is a high variation of the recorded traits between cows but also within cows. Cows always react individually to diseases (Kramer et al., 2009; Lukas et al., 2009; Brandt et al., 2010). In Addition, the sensitivity of mastitis and lameness detection might depend on the different categories of mastitis and lameness. Hence, it is very difficult to detect a unique pattern of cows suffering and/or developing a disease. Caverio et al. (2007) and Miekley et al. (2012) implemented a detection system based on univariate traits. They expect that multivariate monitoring methods might compensate for high variation in each trait und thus improve results of disease detection systems. PCA combined with  $T^2$  as well SPE charts enable such multivariate considerations. Nielen et al. (1995) as well as Sloth et al. (2003) used

PCA to verify whether variation in the data was caused by mastitis and stated its potential for improving multivariate description of bovine udder health. Nielen et al. (1995) found sensitivities and specificities of approximately 75% and 95%, respectively. However, these results were obtained using MEC based on quarter level, leading to better detection performance (Hogeveen et al., 2010). Moreover, no on-line detection system has yet been established compared to the present study. Currently, there is no known PCA utilisation for lameness detection.

Contrary to model-based approaches, e.g. in the studies of de Mol et al. (1999) and Chagunda et al. (2006), PCA does not need an explicit system model (Venkatasubramanian et al., 2003). It is capable of handling high-dimensional and correlated process variables which make them a powerful and easy-to-implement tool for revealing the presence of abnormalities. However, missing values of one of the variables measured at the same time for one cow are critical, leading to omission of all of these traits for this particular time and cow. Due to the comparison between the test and the training dataset, cow-individual analysis, which is e.g. claimed by Lukas et al. (2009) and Miekley et al. (2012), is not possible. In the present study, 100 cows, which were completely healthy during lactation, were used for the training dataset. A higher amount of such cows in the training dataset might cause better detection results and may compensate for this non-individual analysis. However, an enlargement of the training dataset of the present study was not possible.

MacGregor et al. (2005) as well as Kourti (2006) stated that for process monitoring PCA requires a  $T^2$  as well as a SPE chart. Lately, there have been some discussions about combining PCA with other monitoring methods to improve results (Venkatasubramanian et al., 2003). However, there is no solution to this as yet and further research has to be done. For biological processes, as in this study, different monitoring methods might improve detection results and, thus, make PCA applicable for practically implemented disease detection systems. The traits used in the present study (milk yield, milk electrical conductivity, pedometer activity, etc.) have demonstrated their potential for mastitis and lameness detection in several studies (Cavero et al., 2008; Gonzalez et al., 2008; Kramer et al., 2009; Lukas et al., 2009; Miekley et al., 2012). However, the performance of the sensors currently used in practice has recently gained attention. Several studies, e.g. (Nielen et al., 1995; Brandt et al., 2010; Hogeveen et al., 2010), call for improvement of the practically implemented sensors (such as the traits used in this study) as well as future developments in this field to avoid missing or unreliable data in order to enhance the results of monitoring systems.

## 5 Conclusion

The automation of the detection of lameness or mastitis with PCA combined with  $T^2$  and SPE charts, using traits with regard to performance (milk yield, MEC and feed intake) as well as behaviour (feeding behaviour, activity), did not perform well enough for disease detection in dairy cows. The variability of the input parameters between and within cows might have caused high error rates. The performance of the monitoring system might be improved if other monitoring methods or other and more reliable sensor data were to be applied.

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# **CHAPTER THREE**

## **Mastitis detection in dairy cows: An application of support vector machines**

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## **Abstract**

This investigation analysed the applicability of support vector machines, a sub-discipline in the field of artificial intelligence, for the early detection of mastitis. Data used was recorded on the Karkendamm dairy research farm between January 2010 and December 2011. Data of 215 cows in their first 200 days in milk were analysed. Mastitis was specified according to veterinary treatments and defined as disease blocks. The two different definitions used varied solely in the sequence length of the blocks. Only the days before the treatment were included in the blocks. The following parameters were used for the recognition of mastitis: milk electrical conductivity, milk yield, the stage of lactation, the month, the mastitis history during lactation, the deviation from the 5-day moving average of milk electrical conductivity as well as milk yield, and the 5-day moving standard deviation of the same traits. To develop and verify the model of the support vector machines, the mastitis dataset was divided into training and test datasets. Support vector machines are tools for statistical pattern recognition, focusing on algorithms capable of learning and adapting the structure of the input parameters based on the training dataset. The results show that the block sensitivity of mastitis detection considering both mastitis definitions was 84.6%, whilst specificity was 71.6% and 78.3%, respectively. Showing feasible features for pattern recognition of biological data, support vector machines can principally be applied for disease detection. However, without further performance improvement or different study settings (e. g. other indicator variables) support vector machines cannot be easily implemented into practical usage.

**Keywords:** mastitis, early detection, block sensitivity, support vector machines

# 1 Introduction

Mastitis still remains the most frequent and costly disease in the dairy industry, in terms of economics and animal welfare (Kramer et al., 2009). Early detection of and intervention against mastitis reduces veterinary fees, losses in milk yield and milk quality, and increases the cure rate of the infected animals (Milner et al., 1997). With growing herd sizes and the introduction of robotic milking, the classical detection method of visual observations has become more difficult and time-consuming. Thus, there is a need to support the farmer's own observations by improved and automated detection of diseases (de Mol et al., 1997).

In manufacturing industries as well as agricultural science, several quality variables may be controlled simultaneously. In industrial process control, multivariate quality control charts are most appropriate for such situations. In the case of agricultural science and disease detection in particular, practical monitoring due to a large number of false positive alerts as well as too high error rates hinder the application in practice (de Vries and Reneau, 2010; Miekley et al., 2012). In fact, traditional multivariate control charts such as Hotelling's  $T^2$  control charts and multivariate CUSUM or EWMA control charts require that quality characteristics follow a multivariate normal distribution (Montgomery, 2009). However, this may not be reasonable in many real-life applications, where the process distribution is unknown (Ben-Hur et al., 2008). Machine learning, a sub-discipline in the field of artificial intelligence, focuses on algorithms capable of learning and/or adapting their structure (e.g. parameters) based on a set of observed data, with adaptation done by optimizing over an objective or cost function. Machine learning and statistical pattern recognition have been the subject of tremendous interest in the biomedical community because they offer promise for improving the sensitivity and/or specificity of the detection and diagnosis of disease, while at the same time increasing objectivity of the decision-making process (Sajda, 2006). Much of the original excitement for the application of machine learning to biomedicine originated from the development of artificial neural networks (ANNs), which were often proclaimed to be "loosely" modeled on computation in the brain. Cavero et al. (2008), e. g., applied neural networks to monitor udder health. Problematic with ANNs, however, is the difficulty in understanding how such networks construct the desired function and how to interpret the results. Such methods are thus often used as a "black box," with the ANN producing a mapping from input (e.g. medical data) to output (e.g. diagnosis) but without a clear understanding of the underlying function (Sajda, 2006).

To attempt to overcome these difficulties with neural networks, another area in machine learning research has received considerable attention. Support vector machines (SVM) have demonstrated highly competitive performance in numerous real-world applications, such as medical diagnosis, bioinformatics, face recognition, image processing and text mining, thus establishing it as one of the most popular, state-of-the-art tools for knowledge discovery and data mining (Olson and Delen, 2008).

Therefore, the aim of this study was to analyse the applicability of SVMs as a monitoring system for the early detection of mastitis based on practically recorded farm data.

## **2 Materials and Methods**

### **2.1 Data**

Data used was recorded on the Karkendamm dairy research farm between January 2010 and December 2011. During this period, data from 215 cows in their first 200 days in milk (DIM) were available (79,178 milkings). Medical treatments of mastitis were documented constantly by veterinarians and farm staff. Different mastitis categories (e.g. *Staphylococcus aureus* or *Escherichia coli* mastitis) were identified. Due to the low number of diseased cows within these categories, they were combined to cases of mastitis. These cases were defined as the target characteristic to be distinguished from the healthy observation in the data.

Milking took place in a rotary milking parlour manufactured by GEA Farm Technologies. Cows were milked twice daily. Milk yield (MY) and the milk electrical conductivity (MEC) of the composite milk were measured using the Metatron P21 milk meter (GEA Farm Technologies) at every milking.

Besides MY and MEC per milking, further input variables (indicator variables) were successively included into the SVM. The combination of input variables with the best results is presented in the following section. The 5-day moving average for the MEC and MY of the morning and evening milkings for each cow were calculated, respectively, accounting for cow individuality. The deviations in the actual measured observation from the latest moving average value of each cow were then calculated (*dev\_my*, *dev\_mec*). Not only increasing deviations from a moving average of each cow were considered as a sign of mastitis but also an augmentation in standard deviation. This was used to determine the 5-day moving standard deviation for the parameters (*std\_my*, *std\_mec*) of the morning and evening milkings. To provide more detail in the general lactation curve, weeks in lactation (weeks) were divided

into 15 classes (Green et al., 2002; Chuganda et al., 2006). The observations collected within the first 8 weeks of lactation were grouped into weekly intervals. Data from weeks 9 to 16 were grouped into two-week periods, and data taken later than 17 weeks after calving were grouped into four-week periods (Hagnestam-Nielsen et al., 2009). According to Steeneveld et al. (2009), the month of each observation (January: month=1 to December: month=12) and the cow-specific factor of its very own mastitis history are also valuable sources of information. The amount of mastitis cases during the observation period of each cow, referred to as history (history = 0: no mastitis case before/at all), was up to three cases during the cow's first 200 days in milk. In total, nine input variables were used (MEC, MY, dev\_mec, dev\_my, std\_mec, std\_my, week, month, history).

Application of support vector machines necessitates the division of the mastitis into training and test datasets. Hence, two-thirds of healthy animals as well as two-thirds of the animals (Wang et al., 2008) with a disease during the observation period were randomly selected to build the training dataset (Table 1). The remaining one-third in the healthy and diseased dataset were analysed in the test dataset. Descriptive statistical information on the measured traits MY and MEC for the training and test datasets are shown in Table 1.

**Table 1.** Number of all, healthy and ill cows as well as the mean (standard deviations in parenthesis) of the measured variables milk electrical conductivity (MEC) and milk yield (MY) for training and test datasets.

		Train		Test	
<b>Number of cows</b>					
all		150		65	
healthy		115		50	
ill	all	35		15	
	2 cases	8		4	
	3 cases	1		-	
<b>MEC</b>					
(reference units/milking)		491.0	(39.7)	489.8	(35.0)
<b>MY</b>					
(kg/milking)		18.1	(3.8)	18.0	(4.0)

## 2.2 Mastitis definition

Mastitis was defined as disease blocks, i.e. uninterrupted sequences of “days of disease” (Cavero et al., 2008; Kramer et al., 2009). The treatments served as a basis for these disease blocks and the different definitions varied solely on the sequence length of the blocks. As the focus of this study was on early disease detection, only the days before a treatment were included in a disease block (Kramer et al., 2009). If at least one alarm was generated by the monitoring system within the block, it was considered as detected.

Cows were selected for veterinary treatment by the farm staff based on observable signs of mastitis. Two variants of mastitis definition were used in this study:

Mastitis+3: treatment performed including three days before the treatment

Mastitis+4: treatment performed including four days before the treatment

The days in the dataset were classified as “days of health” or “days of disease” based on Cavero et al. (2007). The day of the treatment as well as three or four days before were defined as “days of disease”, respectively. At least seven days after the last treatment of a mastitis case were not utilised for analysis to give consideration to the withdrawal period without any observation. After this period, cows were considered to be healthy. The data contained 64 disease blocks. The distribution of the days of health and days of disease for both mastitis definitions are shown in Table 2.

**Table 2.** Percentage distribution of days of health and days of disease according to the different mastitis definitions considered.

Definition	Training dataset		Test dataset	
	Days of health	Days of disease	Days of health	Days of disease
	[%]	[%]	[%]	[%]
Mastitis+3	99.6	0.4	99.7	0.3
Mastitis+4	99.5	0.5	99.6	0.4

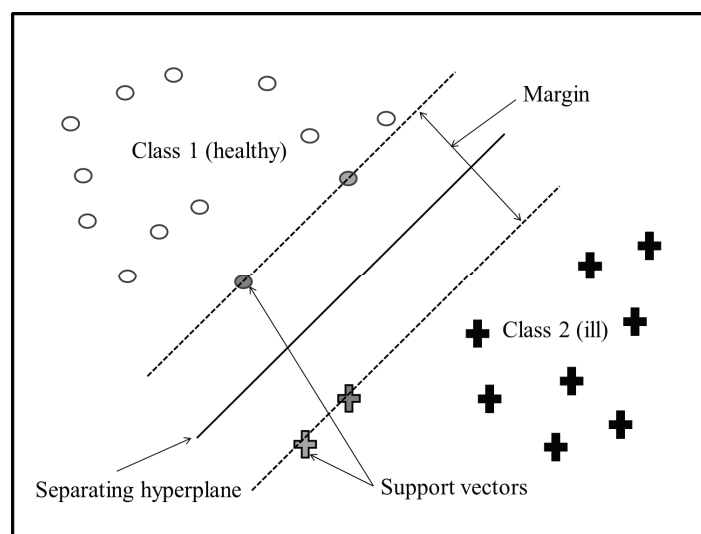


## 2.3. Methods

### 2.3.1 Support vector machines: general concept

The goal of SVM classification is to produce a model (based on the training data) which predicts the target values (i.e. the class labels: healthy or mastitis) of the observed input variables of the test data (i.e. the features). Each instance in the training set contains one target value (healthy or mastitis) and nine input variables.

SVMs discriminate between two (or more) classes by generating a hyperplane (decision boundary or classifier) which optimally separates the classes (Yu et al., 2010) (Figure 1). The easiest separation assumes that the two classes are linearly separable, i.e. there exists a plane that correctly classifies all the points in the two classes. Generally, many linear classifiers are able to separate data into classes. However, only one hyperplane achieves maximum separation. This means that the hyperplane is chosen so that the distance (margin) from the hyperplane to the nearest data point is maximised (Widodo and Yang, 2007) (Figure 1). The nearest data points used to define the margin are called support vectors, represented by the grey circles and crosses (Figure 1). The boundary is entirely defined by these support vectors. In most cases, linear separation between healthy and ill cases of the input data is a restrictive hypothesis of practical use. Non-linearly separable data is mapped into a high-dimensional space in which the transformed data is linearly separable and thus divided by a hyperplane (Olson and Delen, 2008). Mapping into a high-dimensional space can give rise to computational difficulties due to the fact that the dimensionality of the input variable space



**Figure 1.** The margin, separating hyperplane (decision boundary) and support vectors for a two-class classification problem.

explodes exponentially (Bennett and Campbell, 2000). SVMs get around this issue through the use of kernel functions. Kernel functions (usually including linear, polynomial, sigmoid and radial basis functions (RBF)) reduce the complexity of dimensionality by avoiding the step of explicitly mapping the data to a high-dimensional space. This means that the space to be mapped does not have to be known explicitly. The knowledge of the kernel function used is sufficient for all calculations (Schölkopf and Smola, 2001). The key parameters, the penalty parameter  $C$  and the kernel parameters (altogether hyperparameters), need to be pre-selected to generate an optimal SVM model (Yu et al., 2010). The parameter  $C$  controls over-fitting of the model by specifying the tolerance for misclassification. The kernel parameters control the degree of non-linearity of the model (Olson and Delen, 2008). Different kernel functions have differing numbers of kernel parameters. The RBF kernel, for example, has one kernel parameter (gamma) whereas the polynomial kernel has two parameters (gamma and epsilon). Since it is not known which  $C$  and kernel parameters are best for one problem, some parameter selection has to be carried out (Olson and Delen, 2008). A common way is to apply  $v$ -fold cross-validation ( $v$ =number of subsets of the training data). Another recommendation is a “grid-search” using cross-validation. In contrast to cross-validation, “grid-search” does not divide the training dataset into  $v$  subsets of equal size followed by testing the classifier of one subset on the remaining  $v-1$  subsets. In “grid search”, various pairs of the  $C$  and kernel parameters are tried and the one with the best cross-validation accuracy is chosen. For unbalanced data sets, such as in this case (more healthy observations than diseased observations), accuracy may not be a good criterion for evaluating a model. The ROC curve and the related metric area under the ROC curve (AUC) can be more meaningful performance measures since they allow a difference between errors on positive (ill) or negative (healthy) examples (Jin and Ling, 2005). Thus, we selected the best pairs of the  $C$  (best  $C$ ) and kernel parameters (e.g. best gamma) by the pair which achieved the best average area under the curve value. The “grid search” procedure reduces computational costs and it works well for data, such as in this study, which do not have many input variables (Olson and Delen, 2008).

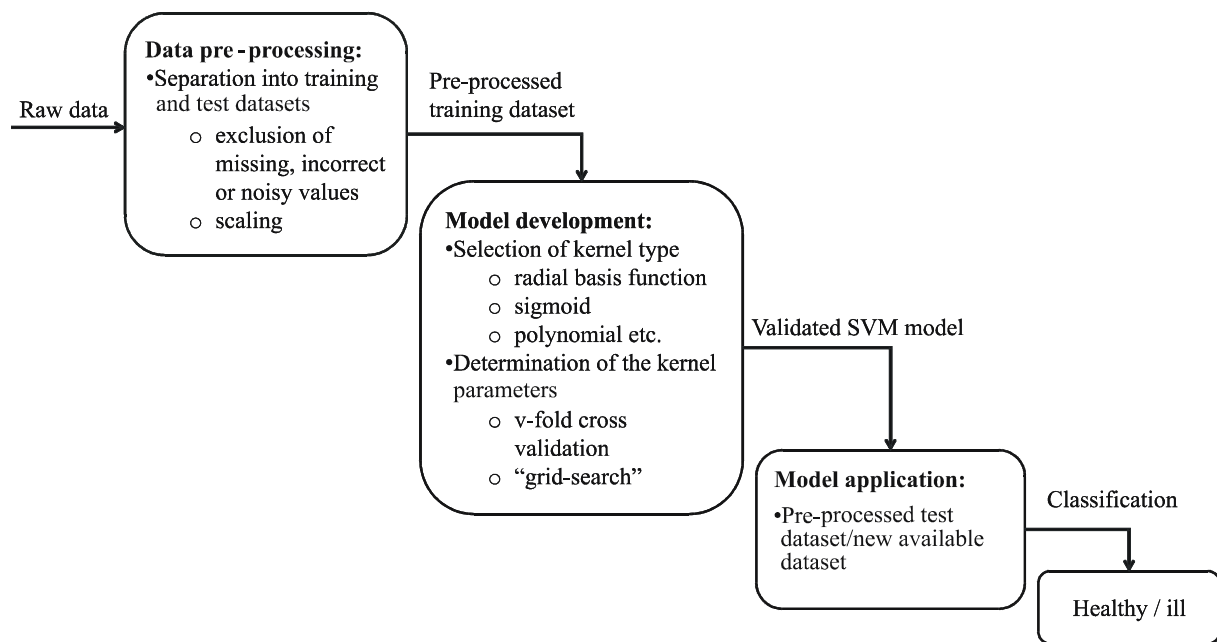
### **2.3.2 Procedure of SVMs in disease detection**

The general procedure for disease detection provided with SVMs is shown in Figure 2. The raw data for mastitis has to be randomly divided into training and test datasets. After pre-processing of both datasets, including the exclusion of missing values and scaling, the training dataset is used for the model development. The first step of the model development is the

selection of the kernel function (e.g. linear, polynomial or radial basis function). For mastitis detection, the radial basis function (RBF) as the kernel function performed best and was therefore chosen for both analysis.

After selection of the kernel type, the parameter C and the kernel parameter gamma (best C and best gamma) have to be determined. In this study, “grid search” with 5-fold cross-validation was applied which is recommended by several studies (Ben-Hur et al., 2008; Olson and Delen, 2008; Chang and Lin, 2011) in the case of data without many variables.

The validated support vector machine model can then be used to predict the health status of each cow in the test dataset.



**Figure 2.** A process description of a SVM for disease detection.

### 2.3.2 Test procedure

System performance was assessed by comparing these predictions provided by the SVMs with the actual occurrence of diseases.

The concerning day of observation was classified as true positive (TP) if the predicted health status corresponded to an actual case of mastitis, while an undetected day of disease was classified as false negative (FN). Each day in a healthy period was considered as a true negative case (TN) if no alerts were generated, and a false positive case (FP) if an alert was given. The performance of these procedures was evaluated by the parameters sensitivity, block sensitivity, specificity, error rate and accuracy.

Sensitivity represents the percentage of correctly detected days of disease of all days of disease as follows:

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

For disease detection, it was not important for all days of a disease block to be recognised, but it was crucial for mastitis to be detected at all and early on. Therefore, block sensitivity was deemed considerably more important than sensitivity. For the block sensitivity, each disease block was considered a TP case if one or more alerts were given within the defined disease block and a FN case otherwise (Cavero et al., 2007; Kramer et al., 2009).

Specificity indicates the percentage of correctly found days of health from all the days of health as follows:

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

Error rate represents the percentage of days outside the disease periods from all the days on which an alarm was produced as follows:

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

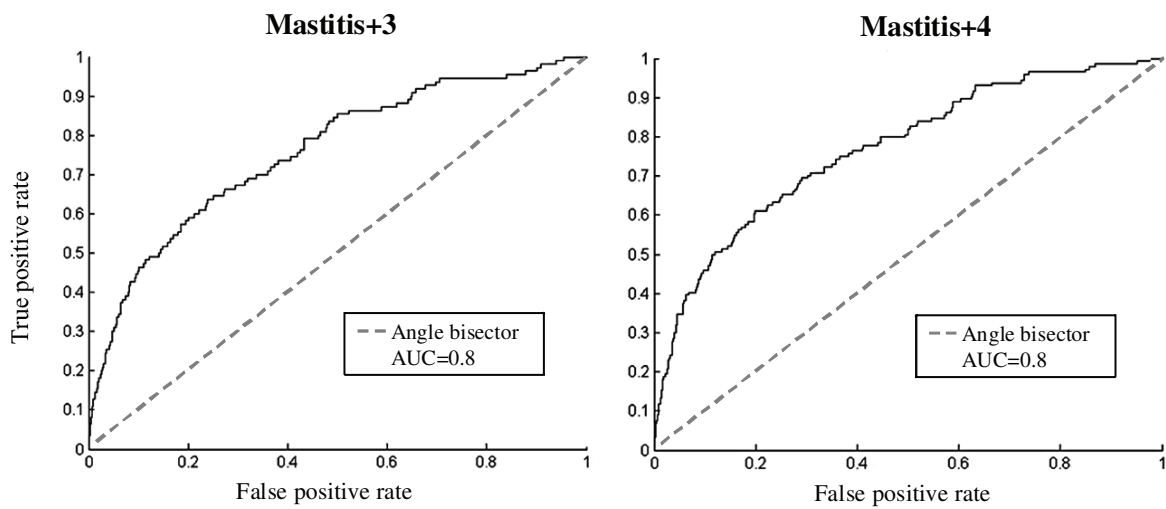
Accuracy measured how correctly the SVM identified a given health status. It indicates the percentage of correctly classified days of health and days of disease from all of the classification results as follows:

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

The number of true positive (TP) as well as false positive (FP) cows per day is also given. TP and FP cows per day signify the average number of rightly and wrongly diseased-registered cows per day, respectively. This is an important detail which indicates for the effort of the mastitis monitoring system.

### 3 Results

The ROC curves of the training datasets providing the best AUC values for (mastitis definitions) Mastitis+3 and Mastitis+4 are shown in Figure 3. Both ROC curves exhibit a slope moving away from the angle bisector. In general, the more distant the ROC curve is from the angle bisector, the greater the ability of the monitoring system to differentiate between healthy and ill animals. The closer the AUC value moves to 0.5 (value of the angle bisector) the poorer the test performs. The ROC curves of Mastitis+3 and Mastitis+4 presented below did not vary much from each other, leading to the best AUC value of 0.8 for both definitions.



**Figure 3.** ROC (receiver operator characteristic) and their corresponding AUC (area under the curve) values for the training process depending on mastitis definition.

These AUC values were determined by different best pairs of the parameter C and gamma kernel parameter depending on the mastitis definitions (Table 3). For Mastitis+3 the best value of C was 64 whereas the best value of gamma was 1. For Mastitis+4, the best value for the cost parameter C was 32. Gamma was calculated to be 4.

The results of the test dataset of each definition are also shown at Table 3. For Mastitis+3, block sensitivity achieved a value of 84.6%, whereas specificity was 71.6%. The error rate, however, was 99.4%. The number of FP cows per day was 4. For the test dataset, the average herd size per day was 17 cows. Therefore, 24% of the animals per day were wrongly classified as ill. Additionally, the accuracy was also provided by the system. For Mastitis+3, the calculated accuracy was 80%.

For the second mastitis definition (Mastitis+4), block sensitivity achieved the same value of 84.6% as the first definition. Showing a value of 78.3%, specificity of Mastitis+4, however, was higher compared to Mastitis+3. The error rate was 99.2%. The number of FP cows per day was also slightly lower than Mastitis+3 (3.6 FP cows per day to 4 FP cows per day). Taking the average herd size into account, 21% of the daily herd would have been mistakenly designated as ill. According to the accuracy of 82.3%, Mastitis+4 performed also slightly better than Mastitis+3.

**Table 3:** Results of mastitis detection for the training and test datasets depending on the two disease definitions

		<b>Mastitis+3</b>	<b>Mastitis+4</b>
<b>Train</b>	<b>Best AUC</b>	0.8	0.8
	<b>Best gamma</b>	64.0	32.0
	<b>Best C</b>	1.0	4.0
<b>Test*</b>	<b>Block sensitivity (%)</b>	84.6	84.6
	<b>Specificity (%)</b>	71.6	78.3
	<b>Error rate (%)</b>	99.4	99.2
	<b>Number of TP cows per day</b>	0.02	0.03
	<b>Number of FP cows per day</b>	4.0	3.6
	<b>Accuracy (%)</b>	80.0	82.3

\*Average herd size: 17 cows per day

## 4 Discussion

The ROC curves and the AUC values (0.8) show that SVMs were able to distinguish between mastitic and healthy animals, on consideration of the training dataset.

According to Kramer et al. (2009), monitoring systems in high-throughput milking parlours, such as in Karkendamm, should reach a block sensitivity of at least 70%. The results indicate that the block sensitivities (84.6%) are above this minimum system requirement for both mastitis definitions. Thus, the detection performance of the monitoring system of both disease definitions can be deemed acceptable. Specificities, however, are only around 80% and below. Additionally, the error rates are too high at about 99%. The error rate is mainly affected by the number of FP alerts, which was also high in the present study, showing more than 20% of the herd per day falsely classified as diseased. This results in more workload for

the farmer accompanied by a loss of confidence in the monitoring system. Such unfavourable results can be caused by several factors.

First, the disease definition is very important and subsequently influences the classification results. In this study, an animal was considered to be ill if a treatment occurred. These treatments were carried out by a qualified veterinarian and can therefore be considered reliable.

According to Hogeveen et al. (2010), an alert should be given before clinical signs are visible so that a treatment has a greater efficiency and reflects the implementations of practice. Therefore, disease blocks were analysed before treatment occurred. Bareille et al. (2003) stated that mastitis effects milk production parameters at three to four days before visual onset of this disease. Thus, three- and four-day periods before clinical signs were chosen for mastitis detection.

However, the choice of the length of the disease blocks has varied widely (1 to 17 days) in past research on disease detection (de Mol et al. 1997; Hogeveen et al. 2010; Kamphuis et al. 2010). For instance, de Mol and Woldt (2001) indicated a period of seven days before mastitis treatment occurred. Cavero et al. (2008) utilised disease blocks of five days (day of treatment plus two days prior and after treatment) for mastitis detection. In general, block sensitivity increases if longer periods are considered. In consequence, a comparison of model performance with other studies is difficult. Other reasons for the obtained results of this study might be attributed to the indicator variables. Due to their easy availability at reasonable costs, the sensor-measured data of MY and MEC have been used in several studies (Cavero et al., 2008; Gonzalez et al., 2008; Hagnestam-Nielsen et al., 2009; Kramer et al., 2009; Lukas et al., 2009). Compared to this study, Cavero et al. (2006), e. g., reached higher block sensitivities (92.9%) and specificities (93.9%) by applying of fuzzy logic. However, the MEC values of Cavero et al. (2006) were measured at the quarter level of each cow, which gives better detection performance (Hogeveen et al., 2010). Additionally, there is a high variation in the recorded traits between cows but also within cows causing a high number of FP cows per day. Cows always react individually to diseases (Kramer et al., 2009; Lukas et al., 2009; Brandt et al., 2010). Hence, it is very difficult to detect a unique pattern in cows suffering and/or developing a disease from the indicator variables. Cavero et al. (2007) and Miekley et al. (2012) implemented a detection system based on univariate traits. They expected multivariate monitoring methods to compensate for high variation in each trait und thus improves the results of disease detection systems.

Support vector machines enable such multivariate considerations. Martiskainen et al. (2009) and Hokkanen et al. (2011) used SVMs to classify cow and calf behaviour, respectively, based on accelerometer data. Both studies stated their potential for pattern recognition and classification. Martiskainen et al. (2009) found an overall sensitivity of the utilised patterns (standing, lying, lame walking) of 66%. According to our knowledge, SVMs have so far not been applied to mastitis detection in dairy cows.

Although the results (which need further improvement) might not seem promising, there are some appealing features of SVMs for disease detection. First of all, SVMs are easy to implement, are able to adapt flexibly to different kinds of classification problems and the final results are stable and reproducible (Bennett and Campbell, 2000). A great advantage of SVMs is the ability to handle unbalanced datasets, which is applicable for many datasets in bioinformatics, especially in disease detection as in this study. Additionally, analyses of more than two different classes, such as in Martiskainen et al. (2009), are possible. Thus, considerations of each mastitis are feasible instead of the division into healthy or mastitis. This might improve the results. However, such approaches necessitate the extension of the training dataset incorporating enough observations of each category or disease. Unfortunately, the main limitation of SVMs is a vast increase in computer and storage time with the number of training examples (Bottou et al., 2007; Ben-Hur et al., 2008). Therefore, the dataset of this study contained data of cows from 2010 to 2011 although more data of previous years were available. Recently, new methods to overcome this problem, called reduced support vector machines (RSVM), have been introduced (Bottou et al., 2007). However, there are some concerns about the test accuracy of the RSVM and further research has to be carried out.

Sensitivity, specificity and error rate are well known quality parameters characterising the performance of a detection system. The sensitivity and specificity of a test, however, are independent of the occurrence of the event (mastitis) to be detected (Hogeveen et al., 2010) giving equal weight to each class (healthy, ill). Nevertheless, the classes are highly imbalanced.



## 5 Conclusion

Support vector machines provide an opportunity for the early detection of mastitis. This classification method has appealing features for its implementation and usage for biological data (e.g. handling of unbalanced data). Although block sensitivities above 70% were achieved, error rates and number of FP cows per day were too high. Given the settings of this study (i. e. indicator variables), SVMs do not seem to be directly implementable into monitoring systems in practice.

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# CHAPTER FOUR

## **Implementation of multivariate cumulative sum control charts in mastitis and lameness monitoring**

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## **Abstract**

This study analysed the methodology and applicability of multivariate cumulative sum charts for early mastitis and lameness detection. Data used was recorded on the Karkendamm dairy research farm between August 2008 and December 2010. Data of 338 and 315 cows in their first 200 days in milk were analysed for mastitis and lameness detection, respectively. Mastitis as well as lameness was specified according to veterinary treatments. Diseases were defined as disease blocks. Different disease definitions for mastitis and lameness (two for mastitis, three for lameness) varied solely in the sequence length of the blocks. Only the days before the treatment were included in the disease blocks. Milk electrical conductivity, milk yield and feeding patterns (feed intake, number of feeding visits and feeding time) were used for the recognition of mastitis. Pedometer activity and feeding patterns were utilised for lameness detection. To exclude biological trends and to obtain independent observations, the values of each input variable were either preprocessed by wavelet filters or a multivariate vector autoregressive model. The residuals generated between the observed and filtered or observed and forecast values, respectively, were then transferred to a classic or self-starting multivariate cumulative sum chart. For mastitis as well as lameness detection requiring a block sensitivity of at least 70%, all of the four combined monitoring systems used revealed similar results within each of the disease definitions. Specificities of 73% to 80% and error rates of 99.6% were achieved for mastitis. The results for lameness showed that the definitions used obtained specificities of up to 81% and error rates of 99.1%. The results indicate that the monitoring systems with these study characteristics have appealing features for mastitis and lameness detection. However, they are not yet directly applicable for practical implementations.

**Key words:** mastitis detection, lameness detection, multivariate cumulative sum charts, wavelets, vector autoregression

# 1 Introduction

In dairy production, the stockman's health management aims at the early detection and intervention of diseases, such as mastitis and lameness. Mastitis and lameness still remain the most frequent and costly diseases in the dairy industry in terms of economics and animal welfare (Kramer et al., 2009). The early detection of and intervention against mastitis and lameness reduces veterinary fees, losses in milk yield and milk quality, and increases the cure rate of the infected animals (Milner et al., 1997).

However, with growing herd size, the classic detection method of visual observations has become more difficult and time-consuming. Thus, there is a need to support the farmer's observations by applying the improved and automated detection of diseases (de Mol et al., 1997). Automated detection is possible using sensor measurements and information from a Management Information System (MIS).

In industrial and chemical production, the concepts of statistical process control (SPC) and more specifically control charts have already been used as one of the major SPC tools (de Vries and Reneau, 2010; Mertens et al., 2011).

The availability of regularly recorded data on the variables of the dairy production processes creates the opportunity to develop such control charts to support the stockman in his daily management tasks (Mertens et al., 2011). Although the concepts of control charts have been approved in agricultural science since 1970s (de Vries and Reneau, 2010), they have not been widely applied in this field. Recently, the use of control charts in livestock production has been regaining interest (Mertens et al., 2011). Lukas et al. (2009) and Miekley et al. (2012), e.g., used self-starting cumulative sum charts (CUSUM) for mastitis detection whereas de Vries and Conlin (2003) used a Shewhart and a classic cumulative sum chart for oestrus detection. However, the charts of these studies are univariate control charts.

In manufacturing industries as well as agricultural science, several quality variables may be controlled simultaneously with one chart taking any correlation between the variables into account (Hawkins and Maboudou-Tchao, 2007; Waterhouse et al., 2010). Therefore, in industrial process control, multivariate quality control charts have been established. Such multivariate methods use the relationship between the components of a multivariate process to generate more powerful algorithms compared to univariate approaches. The aim is to detect changes in the process which can hardly be detected by a univariate attempt (Bodnar and Schmid, 2007)

Numerous multivariate charts and their extensions are presently available. These charts can be grouped into three broad categories, namely, the Hotelling's  $T^2$ , the multivariate exponentially

weighted moving average (MEWMA) and multivariate cumulative sum (MCUSUM) charts. MCUSUM charts have proved particularly powerful (Patel and Divecha, 2010). However, control charts in general are sensitive to trends and autocorrelation within data (Montgomery, 2009). Thus, preprocessing methods, e.g. filters or time series models, play an important role in process control using MCUSUM charts.

Therefore, this paper aims to provide an introduction to the concepts of multivariate cumulative sum charts as well as their applicability in the early detection of mastitis and lameness based on practically recorded farm data. For preprocessing, wavelet filters and multivariate vector autoregressive models were chosen, respectively. Besides the classical MCUSUM chart, a self-starting approach of the MCUSUM will be discussed.

## **2 Material and Methods**

### **2.1 Data**

Data used was recorded on the Karkendamm dairy research farm between August 2008 and December 2010. About 66,000 cow-days from 338 and 315 cows in their first 200 days in milk (DIM) were analysed for mastitis and lameness detection, respectively. Milk parameters (such as milk yield, milk electrical conductivity) have been used for mastitis detection in recent studies (Cavero et al., 2008; Lukas et al., 2009), whereas the activity of cows has been utilised for lameness detection (Kramer et al., 2009). Recently, feed intake and its corresponding behaviour have been reported to be linked to a cow's health status (Gonzalez et al., 2008; Lukas et al., 2008). Therefore, milk electrical conductivity, milk yield and feeding patterns (feed intake, number of feeding visits and feeding time) were used for the recognition of mastitis. Pedometer activity and feeding patterns were utilised for lameness detection.

Milking took place in a rotary milking parlour manufactured by GEA Farm Technologies. Cows were milked twice daily. Milk yield (MY) and milk electrical conductivity (MEC) were measured using the Metatron P21 milk meter (GEA Farm Technologies) at every milking. Activity was measured using pedometers (GEA Farm Technologies), which recorded activity in two-hour periods. The feeding trough was developed and installed by the Institute of Animal Breeding and Husbandry, University of Kiel. Each visit to the feeding troughs was recorded and the amounts of consumed feed were accumulated to daily intakes. Extreme values (mainly for the trait feed intake) which deviated by more than  $\pm 4$  standard deviations were excluded from the dataset. In order to adjust for different timescales between the indicator variables, daily milk yield, weighted MEC per day and average daily activity rates



were calculated (Table 1). Furthermore, high pedometer activity due to documented and progesterone-measured oestrus events was excluded from the dataset.

Medical treatments of diseases were documented constantly by veterinarians and farm staff. Different categories for mastitis (e.g. *Staphylococcus aureus* or *Escherichia coli* mastitis) and for claw and leg diseases (e. g. digital dermatitis or sole ulcer) were identified. Due to the low frequencies of diseased cows within these categories, the categories were combined to form cases of mastitis and lameness, respectively. These cases were defined as the target characteristic to be distinguished from the healthy observation in the data. In case of mastitis, 238 cows without any mastitis treatment during their first 200 DIM as well as 100 treated cows were analysed. The number of treated cows due to lameness was 142.

**Table 1.** Descriptive statistics of the traits showing the number of observations (n), the mean, the standard deviation (std.), minimum (min) and maximum (max) values.

		n	mean	std.	min.	max
<b>Milk yield</b>	kg/day	62,635	36.2	6.1	8.6	70.7
<b>Milk electrical conductivity</b>	reference values	63,703	496.2	34.2	320.0	874.0
<b>Activity</b>	contacts/hour	58,898	30.7	10.0	4.5	70.0
<b>Feed intake</b>	kg/day	48,643	38.5	13.2	2.7	65.8
<b>Time at trough</b>	min/day	48,642	171.2	58.5	13.0	295.0
<b>Trough visits</b>	sum/day	48,647	44.5	15.6	5.2	117.0

## 2.2 Disease definition

Diseases were defined as disease blocks, i.e. an uninterrupted sequence of “days of disease” (Cavero et al., 2008; Kramer et al., 2009). The treatments served as a basis for these disease blocks and the different definitions varied solely by the sequence length of the blocks. As the focus of this study was on early disease detection, only the days before a treatment were included in a disease block (Kramer et al., 2009). If at least one alarm was generated by the monitoring system within the block, it was considered as detected.

### **2.2.1 Mastitis definition**

Cows were selected for veterinary treatment by the farm staff based on observable signs of mastitis infection. Two variants of mastitis definition were used in this study:

Mastitis+3: treatment performed including three days before the treatment

Mastitis+4: treatment performed including four days before the treatment

The days in the dataset were classified as “days of health” or “days of disease” according to Caverio et al. (2007) (Table 2 a). The day of treatment as well as three or four days before were defined as “days of disease”, respectively. To give consideration to the withdrawal period without any observation, at least seven days after the last treatment of a mastitis case were not utilised for the analysis. After this period, cows were considered to be healthy. Combining treatment and three or four days before resulted in 115 mastitis blocks. Besides the number of days of health and days of disease, Table 2a shows the average number of ill and healthy cows per day for both mastitis definitions.

### **2.2.2 Lameness definition**

For veterinary treatment, lame cows were also selected by the farm staff based on observable signs. Lameness was defined using disease blocks analogous to the mastitis definitions. The different definitions varied in the length of the disease blocks.

Lame+3: day of treatment including three days before the treatment

Lame+5: day of treatment including five days before the treatment

Lame+7: day of treatment including seven days before the treatment

All medicated cows were again observed by a veterinarian one week after treatment. Thus, all days between treatment and a follow-up examination were set to “days of disease”. If the follow-up examination proved negative, cows were considered healthy. Otherwise, the period of “days of disease” after the first treatment had to be lengthened for another week. Thus, 210 disease blocks were observed. For all lameness definitions, the number of days of health and days of disease as well as the number of lame and healthy cows per day are shown in Table 2b.

**Table 2.** Number of days of health and days of disease as well as the average number of ill and healthy cows per day according to the different mastitis/lameness definitions considered.

a) Mastitis

Definition	Days of health		Days of disease		Ill cows/day	Healthy cows/day
Mastitis+3	48,138	(99.7 %)	158	(0.3 %)	0.4	78.6
Mastitis+4	48,090	(99.5 %)	209	(0.5 %)	0.6	78.4

b) Lameness

Definition	Days of health		Days of disease		Ill cows per day	Healthy cows/day
Lame+3	39,642	(99.2 %)	340	(0.8 %)	0.5	67.6
Lame+5	39,452	(98.7 %)	519	(1.3 %)	0.7	67.4
Lame+7	39,272	(98.3 %)	696	(1.7 %)	1.0	67.1

## 2.3 Methods

### 2.3.1 Wavelet filters and multivariate vector autoregressive models

Statistical process control (SPC) traditionally assumes that process measurements over time are stationary (without trend) and independent (Montgomery, 2009). Typically, biological data are mostly non-stationary and autocorrelated (Montgomery, 2009; Mertens et al., 2011). In this case, the common approach is to reduce or remove the trend and the autocorrelation from the process by using appropriate time series models or a model-free approach (e.g. filters) and to use the residuals to monitor the process (Montgomery, 2009).

Since the residuals would be stationary and uncorrelated, the assumption of traditional control charts would be satisfied. According to Bodnar and Schmid (2007), multivariate control charts based on residuals simplify the correlation structure and thus the determination of the control design.

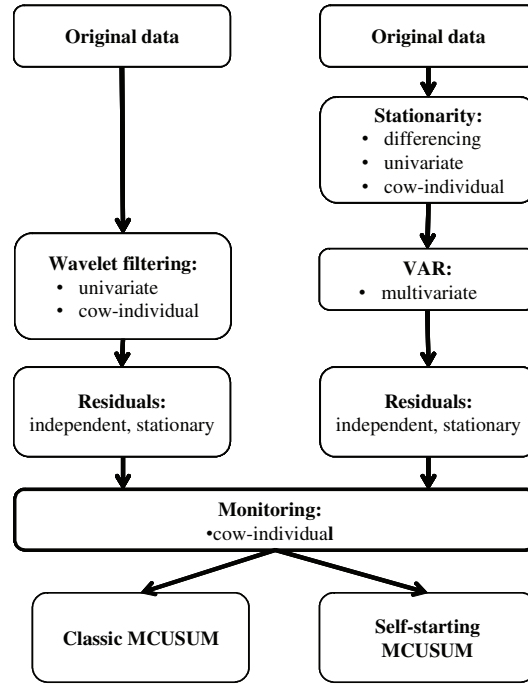
A relatively easy implementable and univariate way of generating residuals using a model-free approach is described by Miekley et al. (2012) using wavelet filters. In short, wavelet filtering identifies trends and noise in the input variable, and then reconstructs this time series without those components. For more detailed information on wavelet analysis, refer to Daubechies (1990), Gencay et al. (2002) and Miekley et al. (2012).

In the present study, the input variables of each cow were individually filtered using Daubechies 4th order wavelet (DB4) for the first filtering step. Residuals (differences

between the observed and filtered values) were calculated and then used for individual monitoring of the cow based on multivariate cumulative sum charts.

In the case of univariate pre-processing of data (e. g. wavelets), possible dependencies between the input variables are not taken into consideration. In multivariate cases, the commonly used multivariate time series model is the vector autoregressive model (VAR) (Luetkepohl, 2007). The VAR model is the extension of the univariate autoregressive model to multivariate data, describing relationships between several time series variables. In this model, each variable not only depends on its past value, but also on the past value of other variables taking the calculated autoregressive parameters into account (Wutsqa et al., 2006; Athanasopoulos and Vahid, 2008). VAR models themselves assume that the input data is stationary (Luetkepohl, 1991; Athanasopoulos and Vahid, 2008). Therefore, in this study, each input variable was differenced (Makridakis et al., 1988). For mastitis and lameness detection, each input variable was differenced once at cow-level to achieve stationarity. Further differencing was not necessary due to over differencing. Then the aim of VAR models is to approximate the actual process resulting in forecast values. These forecast values can be used to generate more reliable but also independent residuals (differences between the observed and forecast value). The multivariate VAR was also applied cow-individually in this study. The resulting residuals were utilised for mastitis and lameness detection for each cow. For more detailed information on multivariate VAR models, refer to Pfaff (2008).

A graphical summary of each step of the monitoring system using wavelet filtering or multivariate VAR models combined with MCUSUM charts is shown in Figure 1. Each succeeding step is based on cow-individual analysis.



**Figure 1.** General procedure of the detection system using either wavelet filtering or vector autoregressive (VAR) models for mastitis or lameness detection with multivariate cumulative sum (MCUSUM) charts.

### 2.3.2 Multivariate cumulative sum charts (MCUSUM)

Two different MCUSUM charts were used to monitor the residuals: (1) the classic MCUSUM and (2) the self-starting MCUSUM chart. Both charts are presented in this section.

Taking the relationship between the indicator variables into account, the aim of the MCUSUM chart in general is to plot multivariate observations over time with one chart to see whether a process is in control, i. e. a cow is healthy.

The multivariate control chart of Pignatiello and Runger (1990), in this study also referred to as classic MCUSUM, is widely used in practical applications due to its good ability to detect shifts of small and medium size in a process of interest (da Cunha Alves et al., 2010). The one-sided multivariate CUSUM chart (MC2, Figure 2) of Pignatiello and Runger (1990) is constructed by

$$MC2_t = \max[0, MC2_{t-1} + D_t^2 - k] \text{ with } MC2_0=0.$$

$D_t^2$  is calculated by

$$D_t^2 = (X_t - \mu)' \Sigma^{-1} (X_t - \mu).$$

$X_t$  denote the  $p \times 1$  vector of the residuals from the input variables (e.g. mastitis: milk yield, milk electrical conductivity, three feeding patterns;  $p=5$ ) at time  $t$  for a single cow. The

MCUSUM assumes that the input variables of  $X_t$  are independent and identically distributed multivariate normal random vectors (Pignatiello and Runger, 1990). The independency is ensured through the use of residuals generated by the methods of the aforementioned section. The residuals were also checked for multivariate normality, which was met by both datasets. The inverse of the covariance matrix is represented by  $\Sigma^{-1}$  whereas  $\mu$  is the mean of each residual input variable from each cow while the animal is considered to be healthy. To establish  $\Sigma^{-1}$  and  $\mu$  based on healthy observations, prior information (Waterhouse et al., 2010) of each cow is needed. Due to the lack of historical data on each cow, both parameters were calculated based on the given datasets. The constant  $k$  is called the reference value, which is related to the magnitude of change to be detected (Pignatiello and Runger, 1990; da Cunha Alves et al., 2010). In the present study,  $k$  was tested for the values of 0.2 to 3.2 and then set to 1.2 for mastitis and lameness detection. To identify when the mean has shifted from the specified values, a control limit is plotted on the charts (Figure 2). It is determined by the  $h$ -value, also called the decision interval. The value of  $h$  was varied from value 0.1 to 18.

In order to run the MCUSUM online without any pre-assumptions about the mean of each cow, a self-starting transformation based on the univariate self-starting CUSUM (Montgomery, 2009) was also applied in this analysis. Self-starting methods update the parameter estimates (mean and variation) with each new observation of each input variable and cow. Both are updated by calculating a running mean and running variation (Hawkins and Olwell, 1998; Montgomery, 2009) at cow-level. The standardisation of each observation, using the running mean and standard deviation of the preceding observations, gives a standardised variate of each input variable at time  $t$ . These variates are then transformed to become independent and follow the standard normal distribution (Montgomery, 2009). Therefore the calculation of  $D_t^2$  changes to

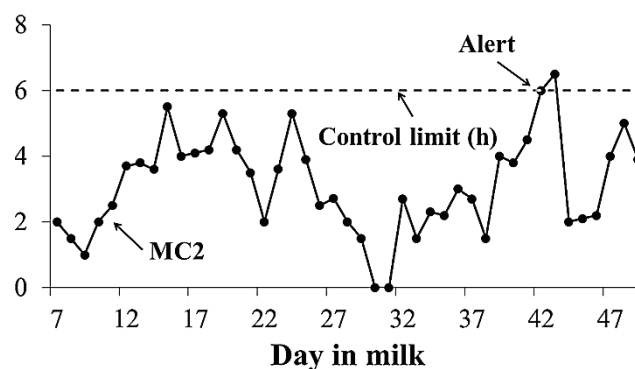
$$D_t^2 = D_t' \Sigma^{-1} D_t .$$

$D_t$  stands for the transformed variates of the residual of each input variable and cow at time  $t$ . For calculation of MC2 at time  $t$ ,  $D_t^2$  was then handled as any  $D_t^2$  for a classic MCUSUM chart and were applied and plotted according to the aforementioned formula. The covariance matrix ( $\Sigma$ ) was the only parameter assumed to be known beforehand. It was calculated in the same way as the classic MCUSUM but this time based on the transformed residuals. The values for the reference value ( $k$ ) as well as the decision interval ( $h$ ) were varied in the same manner as for the classic MCUSUM.

For further information on self-starting transformation for univariate CUSUM charts, refer to Hawkins and Olwell (1998) or Montgomery (2009).

## 2.4 Test procedure

The MCUSUM chart provided an alert whenever values above the control limit of the chart occurred (Figure 2). System performance was assessed by comparing these alerts with the actual occurrence of disease.



**Figure 2.** Example of the multivariate cumulative sum chart (MC2) of Pignatiello and Runger (1990) based on one cow.

The corresponding day of observation was classified as true positive (TP) if the limit was exceeded on a day of disease, while an undetected day of disease was classified as false negative (FN). Each day in a healthy period was considered as a true negative case (TN) if no alert was generated and as 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. Sensitivity represents the percentage of correctly detected days of disease of all days of disease:

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

For disease detection, it was not important for all days of a disease block to be recognised, but it was crucial for mastitis or lameness to be detected at all and early on. Therefore, the block sensitivity was deemed considerably more important than sensitivity. For the block sensitivity, each disease block was considered a TP case if one or more alerts were given within the defined disease block and an FN case otherwise (Cavero et al., 2007; Kramer et al., 2009).

The specificity indicates the percentage of correctly found days of health 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 disease 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 true positive (TP) as well as false positive (FP) cows per day is given. TP and FP cows per day signify the average number of rightly and wrongly diseased-registered cows per day, respectively.

### 3 Results

Working with varying control limits, as in this study, each value generates its own block sensitivity, specificity and error rate. According to Hogeveen et al. (2010), the sensitivity of an automatic milking system should be at least 80%, whereas for milking parlours in which the herdsmen are still present, as in Karkendamm, the sensitivity is lower. Thus, the block sensitivity for mastitis and lameness detection was set to be at least 70%, which is in concordance with Kramer et al. (2009).

Table 3 shows the results for the combined monitoring system wavelet filters and MCUSUM achieving at least 70% block sensitivity. For the first mastitis definition (Mastitis+3), the specificity was 71.4% with an error rate of 99.6%. The amount of FP cows per day was 19.5 animals at an average herd size of around 79.7 cows per day. Compared to Mastitis+3, the second mastitis definition showed better results. At a minimum of 70% block sensitivity (70.2%) the specificity was higher (78.9%) and the number of FP cows per day (14.4 cows) was lower than the first mastitis definition used.

Lameness detection with wavelets and MCUSUM charts (Table 3b) showed more clearly than the mastitis definitions that the longer the disease period under consideration was, the better the monitoring system performed. Lane+3, e.g., revealed the lowest results of all of the lameness definitions. On the other hand, Lane+7 performed best having the highest specificity value, the lowest error rate and lowest number of cows per day falsely detected as ill (10.9 FP cows per day) at an average herd size of 68 cows per day.



**Table 3.** Results of the wavelet filtering combined with classic MCUSUM charts requiring at least 70 % block sensitivity

a) Mastitis\*

	<b>Block sensitivity</b>	<b>Specificity</b>	<b>Error rate</b>	<b>TP cows/day</b>	<b>FP cows/day</b>
Mastitis+3 ( $k=1.2, h=8.0$ )	70.9	71.4	99.6	0.1	19.5
Mastitis+4 ( $k=1.2, h=12.0$ )	70.2	78.9	99.4	0.1	14.4

b) Lameness\*\*

	<b>Block sensitivity</b>	<b>Specificity</b>	<b>Error rate</b>	<b>TP cows/day</b>	<b>FP cows/day</b>
Lame+3 ( $k=1.2, h=3.5$ )	74.2	57.4	99.1	0.2	24.5
Lame+5 ( $k=1.2, h=9.0$ )	71.4	71.1	98.6	0.2	12.9
Lame+7 ( $k=1.2, h=11.0$ )	74.2	81.0	98.2	0.2	10.9

\*Average herd size: 79.7 cows per day

\*\*Average herd size: 68.1 cows per day

**Table 4.** Results of the multivariate VAR models combined with classic MCUSUM charts requiring at least 70 % block sensitivity

a) Mastitis\*

	<b>Block sensitivity</b>	<b>Specificity</b>	<b>Error rate</b>	<b>TP cows/day</b>	<b>FP cows/day</b>
Mastitis+3 ( $k=1.2, h=9.0$ )	76.4	75.5	99.5	0.1	16.7
Mastitis+4 ( $k=1.2, h=12.0$ )	78.9	80.4	99.4	0.1	13.3

b) Lameness\*\*

	<b>Block sensitivity</b>	<b>Specificity</b>	<b>Error rate</b>	<b>TP cows/day</b>	<b>FP cows/day</b>
Lame+3 ( $k=1.2, h=3.5$ )	72.4	63.5	99.2	0.2	19.5
Lame+5 ( $k=1.2, h=6.5$ )	74.3	75.7	98.7	0.2	12.9
Lame+7 ( $k=1.2, h=8.5$ )	73.3	80.1	98.2	0.2	10.5

\*Average herd size: 78.6 cows per day

\*\*Average herd size: 67.3 cows per day

Table 4 displays the results for mastitis (4a) and lameness (4b) detection using the residuals of the multivariate VAR model combined with MCUSUM charts, reaching at least 70% block sensitivity.

The analysis of mastitis detection showed that Mastitis+3 performed more poorly compared to Mastitis+4. The specificity, e.g. of Mastitis+3, was 75.5% with 16.7 FP cows per day whilst the specificity and number of FP cows per day of Mastitis+4 was 80.4% and 13.3, respectively. Considering the specificities and number of FP cows per day, both mastitis definitions analysed by this combined monitoring system revealed slightly better system performance than Mastitis+3 and Mastitis+4 monitored by wavelets and MCUSUM charts (Table 3a).

Lameness results based on VAR (Table 4b) combined with MCUSUM charts show that Lam+5 and Lam+7 differ only marginally from the results of the wavelet and MCUSUM monitoring system.

**Table 5.** Results of the wavelet filtering combined with “self-starting” MCUSUM charts requiring at least 70 % block sensitivity

a) Mastitis\*

	<b>Block sensitivity</b>	<b>Specificity</b>	<b>Error rate</b>	<b>TP cows/day</b>	<b>FP cows/day</b>
Mastitis+3 ( $k=1.2, h=8.5$ )	75.0	72.7	99.6	0.1	18.4
Mastitis+4 ( $k=1.2, h=10.0$ )	70.4	77.4	99.5	0.1	15.2

b) Lameness\*\*

	<b>Block sensitivity</b>	<b>Specificity</b>	<b>Error rate</b>	<b>TP cows/day</b>	<b>FP cows/day</b>
Lame+3 ( $k=1.2, h=3.5$ )	71.9	58.9	99.1	0.2	23.4
Lame+5 ( $k=1.2, h=9.0$ )	71.2	78.2	98.7	0.2	12.3
Lame+7 ( $k=1.2, h=11.0$ )	71.8	81.6	98.2	0.2	10.4

\*Average herd size: 78.2 cows per day

\*\*Average herd size: 67.1 cows per day

The results of the monitoring system based on wavelet filtering in combination with a self-starting MCUSUM (Table 5) reveal that, for both diseases within their definitions, specificities, error rates as well as the number of FP cows per day did not deviate much from the results of wavelets and classic MCUSUM. Mastitis+4 of the self-starting approach for example reached a specificity of 77.4% with an error rate of 99.5% and 15.2 FP cows per day whilst the same definition using wavelets with a classic MCUSUM attained a specificity of 78.9%, an error rate of 99.4% and 14.4 FP cows per day.

Examining the results of the VAR models combined with a self-starting MCUSUM (Table 6) for both diseases shows again that the values achieved are close to the outcome of the VAR and classic MCUSUM chart of each definition used. The findings of Lam+5 at the self-starting analysis, for example, nearly equals the specificity, error rate and the number of FP cows per day of the monitoring system of VAR and MCUSUM charts.

**Table 6.** Results of the multivariate VAR models combined with “self-starting” MCUSUM charts requiring at least 70 % block sensitivity

a) Mastitis*					
	Block sensitivity	Specificity	Error rate	TP cows/day	FP cows/day
Mastitis+3 ( $k=1.2, h=8.5$ )	71.2	74.3	99.6	0.1	17.3
Mastitis+4 ( $k=1.2, h=12.0$ )	70.4	80.7	99.5	0.1	13.0
b) Lameness**					
	Block sensitivity	Specificity	Error rate	TP cows/day	FP cows/day
Lame+3 ( $k=1.2, h=3.5$ )	75.2	62.1	99.1	0.2	20.3
Lame+5 ( $k=1.2, h=7.0$ )	72.7	75.6	98.7	0.2	13.0
Lame+7 ( $k=1.2, h=11.0$ )	74.3	82.9	98.1	0.2	9.1

\*Average herd size: 77.2 cows per day

\*\*Average herd size: 65.1 cows per day

## 4 Discussion

The minimum requirement for the monitoring systems analysed in this study is a block sensitivity of at least 70% (Kramer et al., 2009; Miekley et al., 2012). For both diseases and for all of the four detection systems used (wavelet filtering or VAR combined with a classic MCUSUM or self-starting transformed MCUSUM), block sensitivities were above this system requirement. Thus, the monitoring systems provided sufficient detection performance for mastitis as well as for lameness. Specificities, however, were only around 80% and below. Therefore, the error rates were too high at about 99%. Affecting error rate and specificity, the amount of FP alerts was also high in the present study. The higher the number of FP cows per day, the greater workload the herdsman has, leading to a loss of confidence in the monitoring system. Such unfavorable results obtained by the monitoring systems analysed in this study can be caused by several reasons.

An important part which influences classification results is the disease definition. In this study, an animal was considered to be ill if a treatment occurred. These treatments were carried out by a qualified veterinarian and can therefore be considered reliable. However, cows showing no obvious, visible signs of disease and thus overlooked by the herdsman do exist (Hojsgaard and Friggens, 2010; Kamphuis et al., 2010). Although such cows are ill, they might be classified as false positive cows. To avoid ill but untreated mastitic cows, Miekley et al. (2012) and Kramer et al. (2009) combined treatments with a somatic cell count. Nevertheless, this approach did not lead to better results compared to this study. Classification results can also be influenced by the mastitis or lameness category itself. Due to low number of animals within the categories found or categories without further specification of, e.g. mastitis, the categories were combined to cases of mastitis and of lameness, respectively.

According to Hogeveen et al. (2010), an alert should be given before clinical signs are visible so that treatment has a greater efficiency. Therefore, disease blocks were analysed before treatment occurred. Bareille et al. (2003) stated that mastitis affects milk production at three days whereas feed intake is disturbed by mastitis at around four days before the visual onset of this disease. Thus, three- and four-day periods before clinical signs were chosen for mastitis detection. Up to five days have been reported to identify lameness (e.g. Bareille et al. 2003). Furthermore, Gonzalez et al. (2008) showed that lame cows change their feeding behaviour in a 30-day period before disease occurs. Hence, three-, five- and seven-day periods before clinical outbreak, i.e. an occurrence of the first treatment, were used for lameness detection.

However, the choice of the length of the disease blocks has been widely varied (1 to 17 days) in past research on disease detection (de Mol et al., 1997; Hogeveen et al., 2010; Kamphuis et al., 2010). For instance, de Mol and Woldt (2001) indicated seven days before mastitis treatment occurred. Cavero et al. (2008) utilised disease blocks of five days (day of treatment plus two days prior and after treatment) for mastitis detection. In general, block-sensitivity increases if longer periods are considered. In consequence, a comparison of model performance with other studies is difficult.

Miekley et al. (2012) analysed a univariate mastitis as well as lameness monitoring system. They expected multivariate monitoring methods to possibly improve the results of disease detection systems, which is in concordance with Cavero et al. (2007). Comparing the findings of Miekley et al. (2012) with this study show that for both diseases, especially lameness, sensitivity improved whereas the other performance parameters differ slightly. The reason why the multivariate approach did not outperform the univariate monitoring system can be a result of the indicator variables. Due to their easy availability at reasonable costs, the sensor-measured data of MY and MEC have been used in several studies (Cavero et al., 2008; Gonzalez et al., 2008; Hagnestam-Nielsen et al., 2009; Kramer et al., 2009; Lukas et al., 2009). Compared to this study, Cavero et al. (2006), e. g., achieved higher block sensitivities (92.9%) and specificities (93.9%) by application of fuzzy logic. However, the MEC values of Cavero et al. (2006) were measured at quarter level of each cow, which allowed better detection performance (Hogeveen et al., 2010). Additionally, there is a high variation of recorded traits between cows but also within cows causing a high number of FP cows per day. The performance of the sensors currently used in practice are also criticised and should be improved considerably (Hogeveen et al., 2010). According to Mottram et al. (2002), utilisation of information from biosensors are an opportunity to detect diseases, especially mastitis, more reliably than in currently used monitoring systems. Nevertheless, engineering progress and biological research is needed to integrate biosensors practically (Mottram et al., 2002).

Due to the fact that cows always react individually to diseases, several studies recommend cow-individual analysis (Kramer et al., 2009; Lukas et al., 2009; Brandt et al., 2010). In general, all steps of each combined monitoring system used in this study enable such an approach.

Wavelet filters were able to adapt flexibly to the given input data without prior or additional information (e.g. stage of lactation) on each cow supporting the idea of Kruse et al. (2011) and Miekley et al. (2012) on wavelets as an interesting tool for biological data preprocessing.

However, missing data and necessary adjustments, such as the choice of the filter depth by the scientist, are some drawbacks for wavelets (Gencay et al., 2002; Miekley et al., 2012).

Other than univariate wavelet filters, multivariate VAR models take the relationships among several time series variables into account (Pfaff, 2008). However, multivariate pre-processing methods are not necessarily better than univariate approaches (Chatfield, 2001). Due to the only marginally varying performance parameters between both pre-processing methods and due to the additional need for stationary data, this study comes to the same conclusion as Chatfield (2001).

Currently, there is no known scientific paper dealing with MCUSUM for the health management of livestock. Classic MCUSUM control charts, in general, are easy to implement and provide the herdsman with one performance chart of each cow. For the user, however, it is not obvious which input variable from one chart particularly at the time of an alert might cause the most effect. Additionally, MCUSUM charts do not cope with missing data of one of the input variables leading to omission of all of the existing information of the affected cow at this time (Waterhouse et al., 2010). This circumstance caused a loss of information up to 30% for some cows during their 200 days in milk influencing performance results.

The application of the self-starting transformation on the MCUSUM chart enables monitoring without prior information on each cow. To date, further development of MCUSUM charts, in particular in human health monitoring, is gaining attention (Waterhouse et al., 2010). For self-starting multivariate control charts, this progress in research is currently solely based on multivariate exponentially weighted moving average charts.

## **5 Conclusion**

The automation of the detection of mastitis or lameness with MCUSUM charts using traits with regard to performance (milk yield, MEC and feed intake) as well as behaviour (feeding behaviour, activity), revealed appealing features for individual disease detection in dairy cows. Multivariate extensions from the pre-processing method of wavelet filtering to the usage of VAR did not lead to further performance improvement. Without any changes to the settings of the study, high error rates as well as too many FP cows per day do not yet allow the practical implementation of one of the combined monitoring systems used. Possible enhancement of the performance of the monitoring systems might be achieved by the application of more reliable sensor data and of different input traits.

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# GENERAL DISCUSSION AND CONCLUSION

The main aim of the present study was to detect and quantify special cause variations in the serial data of dairy cows recorded by a management information system (milk yield, milk electrical conductivity, pedometer activity, feeding behaviour, etc.). By the application of different control methods, a computer-assisted early mastitis and lameness detection system should finally be developed. In a first step, a univariate control method was applied based on wavelet filters in combination with either a classic cumulative sum chart or a self-starting cumulative sum chart. Thereafter, particular emphasis was directed to multivariate detection systems: starting with the principal component analysis, applying support vector machines and ending with multivariate cumulative sum charts.

## Disease definition and data

In this thesis, the definitions used for mastitis and lameness varied from *Chapter One* to the following chapters, particularly for the mastitis definitions. In the first chapter, mastitis was defined on the basis of a weekly somatic cell count (SCC), in combination with information gained from udder treatments. The threshold of 100,000 cells/ml was used in the present study for the weekly SCC, 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 (Milch-Güteverordnung, 2004). The reason to include SCC was to avoid the possibility of an oversight of mastitis cases showing no visible signs (Hojsgaard and Friggens, 2010; Kamphuis et al., 2010). Although SCC from quarters or cow samples can be used to predict whether an intramammary infection exists (Dohoo, 2001; Pyörälä, 2003), it can be affected by non-pathological factors such as stage of lactation and milking intervals (Petersen et al., 2005). Comparisons to other studies also using the SCC as part of the mastitis definition are difficult. Other investigations proposed thresholds of 150,000 to 200,000 SCC/ml (Pyörälä, 2003; Windig et al., 2005). 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 and therefore suggested bacteriological investigations of the udder. In the case of lameness, e.g., Pastell and Kujala (2007) used recorded treatments but also a locomotion scoring system to ensure lameness. However, gait scoring is subjective with a low inter- and intra-observer repeatability (37% and 56%) (Pastell and Kujala, 2007). Therefore, all of the mastitis and lameness definitions used in the further chapters were solely based on veterinary secured

treatments differing in the length of the time blocks for the animals to be considered as ill before the first treatment (Bareille et al., 2003; Gonzalez et al., 2008; Kramer et al., 2009). Another reason to change the mastitis definition was the high amount of missing data of up to 30% within each cow for the datasets of *Chapters Two* and *Four*. This led to starts of disease blocks based on SCC without any observations and, thus, non-detectable cases of mastitis of up to 70%.

## Performance evaluation

The model performance was assessed by comparing the alerts provided by the system with the actual occurrences of mastitis and lameness. Block sensitivity, specificity and error rate were evaluated as performance parameters. Depending on the disease definition used, block sensitivity considered whether one or more alerts were given within the block before the first treatment. The choice of the length of this period, so-called time windows, is decisive, since block sensitivity increases if longer periods are considered (Kramer et al., 2009; Hogeveen et al., 2010). However, it was difficult to compare the results found in this thesis with previously reported results due to the large variation in applied time windows in the different studies. Additionally, block sensitivity and specificity are interdependent, which is crucial when applying control charts (*Chapter One, Two* and *Four*). The optimal control limit can be chosen depending on the use of the method determining whether a high sensitivity or a high specificity is desired. According to Hillerton (2000) and Hogeveen et al. (2010) the sensitivity of automatic milking systems should be at least 80%, whereas for high throughput milking parlours where the herdsman is still present, such as the one in Karkendamm, the sensitivity is lower. Thus, the block sensitivity for mastitis and lameness detection was set to be at least 70%, which is in concordance with Mein and Rassmussen (2008), Kramer et al. (2009) and the International Standard ISO/FDIS 20966 (ISO, 2007). However, the sensitivity level of a detection model when implemented in practice is still discussed critically (Hogeveen et al., 2010). International agreements on biologically appropriate and practically relevant requirements (time windows, sensitivity level) to validate disease detection models are therefore still needed.

Sensitivity, specificity, accuracy and error rate are well-known quality parameters. Nonetheless, they are independent of the occurrence of the event (mastitis or lameness) to be detected (Hogeveen et al., 2010) giving equal weight to each class (healthy, ill). The proportion between days of disease and days of health of mastitis as well as lameness is low,

leading, e.g., to high error rates. To account for this, some authors recommend the use of different quality parameters such as the success rate for evaluation, taking the prevalence of a disease into account (Sherlock et al., 2008; Hogeveen et al., 2010). A disadvantage of such an approach is that it is not an 'absolute' statistic varying due to seasonal and management changes and between farms.

## **Process control methods**

The univariate detection of mastitis and lameness was performed in *Chapter One*. Daily milk electrical conductivity was used for mastitis monitoring, whereas average pedometer activity per day was considered to be the input variable for lameness detection. However, the results of the univariate monitoring systems, especially for lameness, hinder implementation into practice. Several studies expect that performance of the monitoring system would improve if more traits, i.e. multivariate considerations, were included (de Mol et al., 1997; Cavero et al., 2007; Lukas et al., 2009; Mertens et al., 2011). Therefore, three multivariate monitoring methods from various sectors such as biomedical diagnosis, bioinformatics, industrial and chemical process control were applied: (1) principal component analysis (PCA) in combination with a Hotelling's  $T^2$  and residual chart, (2) support vector machines (SVM) and (3) wavelet filters or multivariate VAR models, respectively, fused with either a classic multivariate cumulative sum chart (MCUSUM) or a self-starting MCUSUM. Although improvement in the findings from the univariate approach was seen especially for lameness detection, none of these multivariate methods was superior to the others.

Although different in methodology, one problem was an issue in all the three multivariate methods. Missing values of one of the input variables measured at the same time for one cow were critical, leading to the omission of all of these traits for this particular time and cow (Bottou et al., 2007; Kourti et al., 2009; Waterhouse et al., 2010) – particularly in the case of *Chapter Two* and *Four*. For the second chapter, the problem with missing observations can be slightly attenuated by the fact that the methods used are solely based on snapshots by comparing the data of the test dataset of one animal at one time of event against the training data characteristics. This implies that neither PCA nor the  $T^2$  and the residual charts make use of prior information during the time series of each cow (MacGregor and Kourti, 1995; Sullivan, 2008; Kourti et al., 2009). However, the large between-cow variability having the same health status aggravates disease detection based on a training dataset incorporating completely healthy cows which are not included in the test dataset (de Mol, 2000). Even

though prior information gathered for each cow would be available for usage of each cow as its own control, these observations must be in a state of health (in-control) (Kourti et al., 2009) which might not be applicable for all cows.

The support vector machines (SVM) applied in *Chapter Three* also work with a training dataset. Different to the aforementioned method, SVM also take both the days of health and the days of disease into account at the same time considering the imbalance between these two classifications (Bottou et al., 2007). Besides the ability of processing imbalanced datasets, SVM is the only method presented in this study capable of handling measured time series data as well as non-sensor information, e.g. mastitis history and stage of lactation. Mottram et al. (1997) as well as Steeneveld et al. (2010) suggested that an improved mastitis detection can be expected when sensor information is combined with non-measured cow information. The input variables used in this thesis (sensor and non-sensor data) were successively included into the method. The combination of input variables with the best results of block sensitivity and specificity is presented in this study. Comparing these findings for mastitis to the other methods presented in this thesis show that SVM reached the highest block sensitivities with similar values of specificities. Therefore, these results support the proposal of Mottram et al. (1997) and Steeneveld et al. (2010) of handling both kinds of information for disease detection. SVM for lameness detection was also carried out based on pedometer activity and similar non-sensor cow information with regard to mastitis. However, the trained patterns found could not be transferred to the test dataset. Martiskainen et al. (2009) and Hokkanen et al. (2011) applied SVM to classify cow and calf behaviour, respectively, based on three-dimensional accelerometer data. Both studies stated their potential for pattern recognition and classification. Due to the fact that SVM were able to classify the data based on this activity observation, the one-dimensional measured pedometer activity was not sufficiently informative. When compared to the other monitoring methods, SVM are more complex and they do not provide an overview of the performance, i.e. a control chart, of each cow to the herdsmen. This might result in the total exclusion in decision-making and understanding of the method to some farmers as a manager. The main limitation of SVM, however, is a fast increase in computing and storage time with the number of training examples (Bottou et al., 2007; Ben-Hur et al., 2008).

Regarding the experiences of the aforementioned methods, the last chapter explored monitoring methods with special emphasis on cow-individuality, easy implementation and involvement of the farmer. MCUSUM charts can theoretically accomplish these demands. Especially the self-starting approach enables monitoring without prior information

(Montgomery, 2009). The MCUSUM chart, like the univariate CUSUM, is a memory charts which can rely on the preceding observation during monitoring. This memory turns the MCUSUM into a more sensitive chart than the charts presented in *Chapter Two* (Lowry and Montgomery, 1995; Montgomery, 2009). The difficulty with this memory arises if datasets with missing data are used, as in this study. The onset of charting, e.g. after a restart due to missing values, reduces the performance of the charts significantly (Hawkins and Olwell, 1998). Applying a multivariate CUSUM chart to such kind of data always necessitates pre-processing to fulfil the assumptions of the chart (Montgomery, 2009). Preserving cow-individually, wavelet filters for example have proved to be a flexible tool without increase in computing and storage time.

### **Further development and prospects**

The results of the methods used in this thesis are characterised by a high number of false positive cows per day restricting the one-to-one transfer into practical health monitoring. However, these methods work well in other areas of process control, such as industrial and chemical fault detection (Choi et al., 2005; Kourti et al., 2009), medical diagnosis (Waterhouse et al., 2010; Yu et al., 2010) and even other classification analyses in agriculture (Lukas et al., 2009; Martiskainen et al., 2009; Hokkanen et al., 2011). Thus, the results can be influenced by the indicator variables. The indicator variables applied in the present study are used in several studies, especially milk yield and milk electrical conductivity, (Cavero et al., 2008; Gonzalez et al., 2008; Hagnestam-Nielsen et al., 2009; Kramer et al., 2009; Lukas et al., 2009). They are already easily available at reasonable costs on most of the farms or are gaining interest (feeding patterns). However, the performance of the sensors currently used in practice should be improved considerably (Hogeveen et al., 2010). Due to the high amount of missing data or biologically impossible values found in this study, we agree with this. Mottram et al. (2002) suggested a different approach utilising information from biosensors. According to Mottram et al. (2002), such sensors are an opportunity to detect diseases, especially mastitis, more reliably than in currently used monitoring systems measuring more disease-related variables. Nevertheless, engineering progress and biological research is needed to integrate biosensors practically (Mottram et al., 2002).

The methods used in this thesis were tested solely on one farm. Usually, a limited number of farms and a small number of cases are included in studies on disease detection. For example, Maatje et al. (1992) and Norberg et al. (2008) all used one (research) farm to record data.

These approaches of using one herd for the development of detection methods may result in a model that detects disease at high levels of sensitivity and specificity, but fails with data of a new farm (Hogeveen et al., 2010). Another disadvantage is that the small number of mastitis and lameness cases included may not represent all variations in the diseases' characteristics (in terms of clinical signs and sensor data), causing a drop in the detection performance of the developed model (Hogeveen et al., 2010; Kamphuis, 2010). The extension of the analysis to other farms was also tried in this thesis. Incompatible units of the same input variable or non-existent variables at different farms prevented further investigations. Nevertheless, databases incorporating several farms are attractive for detection methods based on training datasets, e.g., allowing sub-databases for disease categories or for farms in holding, size or yield.

Before application on a large scale in practice, it is essential to explore several economically attractive implementation strategies by cost-benefit analysis. In addition to the quality parameters (sensitivity, error rate, specificity), this would give another but not less important point of view on the evaluation of monitoring systems. These economical valuations are one of the major reasons for the herdsmen to decide for or against management software and sensors. There are no such studies available at present and, thus, they present interesting concepts for further research.

## **Conclusion**

Overall, it can be concluded that it is not possible to have a fair and sensible comparison between results found in this study and results reported in previous studies. The reasons for this are the large variation in definitions, the variation in applied time windows, the different evaluation characteristics used, and the differences in data inclusion criteria and quality of sensors used for analyses. For detection models, the recommended block sensitivity of more than 70% complies with the monitoring systems using currently available sensor data as well as non-sensor measured data. When viewed on their own, all of the methods used have appealing features for mastitis and lameness analyses. SVM, e.g., are able to utilise non-sensor information but lack cow-individuality. MCUSUM charts operate with serial sensor data but enable important cow-individuality at every step of this detection system. Nevertheless, the perfect detection model directly implementable into practical monitoring systems of dairy farms has not been developed in this thesis. The reasons for the unsatisfying results may not have been due to the underlying methods used, but must instead rather focus on the indicator variables used. In order to obtain practical monitoring systems as an aid for



the herdsmen, focus should be given to research into international agreements on standardised definitions and into sensor techniques which measure more reliably as well as more mastitis- and lameness-related variables.

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# GENERAL SUMMARY

Due to growing herd sizes, the classic disease detection method of visual observations has become more difficult and time-consuming. Therefore, monitoring the performance of dairy cows is increasingly based on automatic sensors. However, there is still a need for management support systems to give reliable and understandable alarms to the herdsmen at the onset of disease. The aim of the current study was to detect and quantify special cause variations in the serial data recorded by management information systems (milk yield, milk electrical conductivity, pedometer activity, feeding behaviour, etc.) and to finally develop a computerised mastitis and lameness detection system by the application of different control methods.

Data for the analysis was recorded on the Karkendamm dairy research farm of the University of Kiel between August 2008 and December 2011. Three different datasets were used for the analysis in the four chapters.

The first part of the thesis (*Chapter One*) assessed the potential to detect mastitis and lameness based on univariate traits. The time series of milk electrical conductivity per day and average daily pedometer activity were analysed at cow-level for the detection of mastitis and lameness, respectively. Mastitis was determined according to the definitions: (1) udder treatments, (2) udder treatments or somatic cell count above 400,000 cells/ml and (3) udder treatments or somatic cell count above 100,000 cells/ml. Lameness treatments were used to determine two definitions of lameness differing in the length of the corresponding disease block. Two different univariate monitoring systems were applied: (1) wavelet filters combined with a classic cumulative sum chart and (2) wavelet filters in combination with a self-starting cumulative sum chart. A comparison between the detection performances of the two monitoring systems was conducted according to block sensitivity, specificity and error rate. If the block sensitivity was set to be at least 70%, the specificities of mastitis detection ranged between 59.2% and 82.8% and the error rates varied between 69.2% and 99.6% depending on the mastitis definition and cumulative sum chart used. In the case of lameness detection, none of the definitions were able to reach a block sensitivity of more than 70%. For both diseases, the self-starting cumulative sum charts achieved higher specificities and, thus, lower false positive cows per day than the classic approach.

The aim of the second chapter (*Chapter Two*) was to describe the applicability of principal component analysis (PCA) combined with the Hotelling's  $T^2$  chart and the residual control chart for process monitoring. This time, mastitis as well as lameness was specified according to veterinary treatments. The different definitions used (two for mastitis, three for lameness) varied solely in the sequence length of the blocks. These disease definitions were also appropriated for the remaining chapters. Milk electrical conductivity, milk yield and feeding patterns (feed intake, number of feeding visits and feeding time) were used for the recognition of mastitis. Pedometer activity and feeding patterns were utilised for lameness detection. Block sensitivity of mastitis detection ranged from 77.4% to 83.3%, whilst specificity was around 76.7%. The error rates were around 98.9%. For lameness detection, the block sensitivity varied from 73.8% to 87.8% while the obtained specificities were between 54.8% and 61.9%. The error rates fluctuated between 87.8% and 89.2%. Despite better performance for lameness detection than the univariate approach, PCA does not yet seem practically applicable.

The third chapter (*Chapter Three*) investigated the efficiency of support vector machines (SVM) for the early detection of mastitis. Mastitis alarms were provided by this monitoring system using milk yield, milk electrical conductivity and further cow-individual information such as stage of lactation and mastitis history as input variables. To develop and verify the model, the dataset was randomly divided into training and test data subsets. The learned patterns for mastitis based on the training dataset were used for mastitis detection in the test dataset. Block sensitivity of both mastitis definitions were 84.6% whereas the specificities ranged from 71.6% to 78.3% with error rates of 99.2%.

In comparison with the aforementioned control methods, support vector machines have appealing features for mastitis detection. However, the results obtained hinder one-to-one implementation in practice.

*Chapter Four* deals with multivariate cumulative sum control charts. The datasets as well as input variables of *Chapter Two* were utilised for mastitis and lameness detection. To exclude biological trends, the values of each input variable were either preprocessed by wavelet filters or a multivariate vector autoregressive model. The residuals generated were then transferred to the classic and self-starting multivariate cumulative sum charts, respectively. Requiring a block sensitivity of at least 70%, all of the four combined monitoring systems used revealed similar results within each of the disease definitions. For mastitis detection, the specificities

were 73% to 80% with error rates of 99.6%. For lameness, specificities of around 81% and error rates of 99.1% were obtained. Although showing a marginal improvement over *Chapter One*, the results achieved in this chapter indicate that the monitoring systems working with these study characteristics are also not yet practically applicable.

The findings in this study illustrate the complexity of mastitis and lameness. In order to obtain practical monitoring systems, research should be focused on sensor techniques which measure more reliably as well as more mastitis- and lameness-related variables.





# ZUSAMMENFASSUNG

Die auf Tierbeobachtungen beruhend klassische Erkrankungskontrolle ist aufgrund steigender Herdengrößen erschwert. Diese Tendenz führt dazu, dass das Monitoring von Milchkühen immer mehr auf automatisierten Sensormessungen, insbesondere während des Melkprozesses, basiert. Die Entwicklung von computergestützten Hilfssystemen für eine zuverlässige und eindeutige Alarmmeldung zu Erkrankungsbeginn stellt jedoch eine der Herausforderungen im Gesundheitsmonitoring der Milchkuh dar. Ziel der vorliegenden Arbeit war es, gerichtete Abweichungen in seriellen Daten eines Management-Information-Systems (Milchleistung, elektrische Leitfähigkeit, Aktivität, Futteraufnahme, etc.) zu detektieren, um ein Monitoringsystem zur Früherkennung von Mastitis und Lahmheiten zu entwickeln.

Die Datenerfassung erfolgte auf dem Versuchsbetrieb Karkendamm der Christian-Albrechts-Universität zu Kiel von August 2008 bis Dezember 2011. Drei unterschiedliche Datensätze wurden für die Auswertungen in den vier Kapiteln verwendet.

Im ersten Kapitel wird eine univariate Methode zur Mastitis- und Lahmheitsdetektion vorgestellt. Kuhindividuelle Zeitreihen der elektrischen Leitfähigkeit der Milch pro Tag sowie der täglichen Pedometeraktivität wurden als Indikatorvariablen für Mastitis und Lahmheit genutzt. Drei unterschiedliche Mastitisdefinitionen wurden verwendet: (1) Mastitisbehandlungen, (2) Mastitisbehandlungen oder somatischer Zellgehalt über 400.000 Zellen/ml und (3) Mastitisbehandlungen oder somatischer Zellgehalt über 100.000 Zellen/ml. Behandlungen aufgrund von Lahmheit wurden für die Erstellung von zwei Definitionen herangezogen, die sich nur in der Länge des jeweiligen Erkrankungsblockes unterschieden. Zwei unterschiedliche, univariate Monitoringsysteme kamen zu Anwendung: (1) Wavelet-Filter in Kombination mit einem klassischen kumulierten Summen-Chart (CUSUM) und (2) Wavelet-Filter verknüpft mit einem sogenannten selbststartenden CUSUM-Chart. Block-Sensitivität, Spezifität und Fehlerrate wurden zur vergleichenden Evaluierung der beiden genutzten Monitoringsysteme verwendet. Bei einer Block-Sensitivität von mindestens 70 % erreichte die Spezifität in Abhängigkeit der verwendeten Mastitisdefinition und des jeweiligen Charts Werte zwischen 59,2 % bis 82,8 %. Die Fehlerraten variierten von 69,2 % bis 99,6 %. Die Lahmheitserkennung hingegen realisierte in keiner Untersuchung eine Block-Sensitivität über 70 %. Für die Betrachtungen beider Erkrankungen gilt, dass der selbststartende Chart höhere Spezifitäten und somit eine geringere Anzahl falsch positiver Kühe pro Tag erreichte als der klassische CUSUM-Chart.

Das Ziel des zweiten Kapitels ist die Anwendung von der Principal-Component-Analyse in Verbindung mit dem Hotelling's  $T^2$ - sowie dem Residuen-Chart. Mastitis- und Lahmheitserkrankungen wurden alleinig aufgrund der erfolgten veterinärmedizinischen Behandlungen definiert. Die Definitionen (zwei für Mastitis und drei für Lahmheit) unterschieden sich nur in der Blocklänge vor der ersten Behandlung und wurden ebenfalls in den folgenden Kapiteln genutzt. Die Milchleistung, die elektrische Leitfähigkeit der Milch sowie verschiedene Fütterungsparameter (Futtermittelaufnahme, Anzahl Trogbesuche und Verweildauer am Trog) wurden als Indikatorvariablen für ein Mastitismonitoring verwendet. Die Pedometeraktivität sowie die zuvor genannten Fütterungsparameter dienten der Lahmheitserkennung. Während die Block-Sensitivitäten der Mastitisedektion Werte von 77,4 % bis 83,3 % aufwiesen, lagen die Spezifität und die Fehlerraten bei 76,7 % bzw. 98,9 %. Die Block-Sensitivitäten der Lahmheitsauswertungen variierten von 73,8 % bis 87,8 %, mit Spezifitäten von 54,8 % bis 61,9 % und Fehlerraten zwischen 87,8 % und 89,2 %. Trotz einer Verbesserung der Detektionsergebnisse, vor allem für die Lahmheitserkennung, ist dieses Monitoringsystem für eine praktische Implementierung nicht geeignet.

Im dritten Kapitel wird die Anwendbarkeit von Support-Vector-Machines für eine Mastitisfrüherkennung untersucht. Die Auswertung basierte sowohl auf der Milchleistung, der elektrischen Leitfähigkeit als auch auf weiteren kuhindividuellen Indikatorvariablen, wie zum Beispiel dem Laktationsstadium und der Information über Mastitis-Vorerkrankungen. Die Modellentwicklung und -überprüfung erforderte die zufällige Einteilung der Tiere in einen Trainings- sowie einen Testdatensatz. Die aus dem Trainingsdatensatz erlernten Erkrankungsmuster wurden dann zur Mastitiserkennung in den Testdatensatz transferiert. Im Fall beider Mastitisdefinitionen wurde eine Block-Sensitivität von 84,6 % erreicht. Die Spezifität schwankte hingegen zwischen 71,6 % und 78,3 % mit einer Fehlerrate von 99,2 %. Obgleich Support-Vector-Machines für Auswertungen mit dem Ziel der Mastitisedektion im Vergleich zu den vorhergehenden Methoden attraktive Einstellungsmöglichkeiten bieten, erlauben auch hier die erreichten Ergebnisse keine direkte praktische Anwendung.

Das letzte Kapitel beschäftigt sich mit multivariaten kumulierten Summen-Charts (MCUSUM). Sowohl für die Mastitis- als auch Lahmheitserkennung wurde der jeweilige Datensatz und dessen Indikatorvariablen des zweiten Kapitels verwendet. Um biologische Trends aus den Daten auszuschließen, wurden die tierindividuellen Beobachtungswerte entweder mittels Wavelet-Filter oder multivariaten vektor-autoregressiven Modellen

vorverarbeitet. Die generierten Residuen wurden dann in einen klassischen bzw. selbststartenden MCUSUM-Chart überführt. Bei einer Block-Sensitivität von mindestens 70 %, zeigten alle vier untersuchten Methoden innerhalb der Erkrankungsdefinitionen ähnliche Ergebnisse. Die Mastitisauswertungen erreichten Spezifitäten von 73 % bis 80 % und Fehlerraten von 99,6 %. Die Spezifitäten und Fehlerraten der Lahmheitsanalyse betrugen 81 % beziehungsweise 91 %. Auch wenn eine leichte Verbesserung im Vergleich zu den univariaten Methoden festgestellt werden konnte, lassen die Ergebnisse eine Überführung der in diesem Kapitel vorgestellten Monitoringsysteme in den praktischen Bereich der Erkrankungsfrüherkennung nicht zu.

Insgesamt veranschaulichen die Ergebnisse die Komplexität von Mastitis- und Lahmheitserkrankungen. Damit die untersuchten Monitoringsysteme praktisch implementiert werden können, sind eine Verbesserung und Weiterentwicklung der Sensortechnik für die Erhebung zusätzlicher mastitis- und lahmheitsrelevanter Indikatorvariablen erforderlich.



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