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Application of CUSUM charts to detect lameness in a milking robot

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Abstract

In the year 2006 about 4000 farms worldwide used over 6000 milking robots. With increased automation the time that the cattle keeper uses for monitoring animals has decreased. This has created a need for automatic health monitoring systems. Lameness is a crucial welfare and economic issue in modern dairy husbandry. It causes problems especially in loose housing of cattle. This could be greatly reduced by early identification and treatment.

A four-balance system for automatically measuring the load on each leg of a cow during milking in a milking robot has been developed. It has been previously shown that the weight distribution between limbs changes when cow get lame. In this paper we suggest CUSUM charts to automatically detect lameness based on the measurements. CUSUM charts are statistical based control charts and are well suited for checking a measuring system in operation for any departure from some target or specified values. The target values for detecting lameness were calculated from the cow's own historical data so that each animal had an individual chart.

The method enables objective monitoring of the changes in leg health, which is valuable information in veterinary research because it provides means for assessing the severity and impact of different causes of lameness and also evaluating the effect of treatment and medication. So far no objective method for calculating these measures has been available and the methodology presented in this paper seems very promising for the task.
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Keywords: Lameness detection; Livestock weighing; Dairy cattle; Statistical quality control

1. Introduction

Automatic milking has become a common practice in dairy husbandry and in the year 2006 about 4000 farms worldwide used over 6000 milking robots (de Koning, 2006). There is a significant movement with the objective of fully automating every process from feeding to milking.

Increase in automation is a consequence from increasing farm sizes, the growth of labour costs, demand for more profit and more efficient production as well as the need for free time for the farmers. As the level of automation increases, time that the cattle keeper uses for monitoring animals decreases. This has created a need for systems for automatically monitoring the health for farm animals. The popularity of milking robots also offers a new and unique possibility to monitor animals in a single confined space up to four times daily.

Lameness is a crucial welfare issue in modern dairy industry. Limb disorders cause serious welfare, health and economic problems especially in loose housing of cattle (Juarez, Robinson, DePeters, & Price, 2003; Klaas, Rousing, Fossing, Hindhede, & Sorensen, 2003). Lameness causes losses in milk production (Green, Hedges, Schukken, Blowey, & Packington, 2002; Warnick, Janssen, Guard, & Grohn, 2001) and leads to early culling of animals (Enting, Kooij, Dijkhuizen, Huirne, & Noordhuizen-Stassen, 1997). These costs could be reduced with early identification and treatment (Green et al., 2002).

Most common way to assess lameness still today is visual inspection with locomotion scoring systems (Manson & Leaver, 1988; Sprecher, Hostetler, & Kaneene,

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1997). The use of these systems requires expertise and they have been shown to be subjective (Winckler & Willen, 2001). Studies also show that farmers only recognize 25% of lame animals (Whay, Main, Green, & Webster, 2003).

A four-balance system for automatically measuring the load on each leg of a cow during milking in a milking robot has been developed at the University of Helsinki (Pastell et al., 2006; Pastell & Kujala, 2007). It has been shown that the system can be used to detect lameness based on the weight distribution between limbs and a Probabilistic Neural Network model to detect lameness cases has been developed (Pastell & Kujala, 2007). However there is a clear need to develop a model which can be used to evaluate the duration and the magnitude of the problem and adapt its behavior for individual animals.

CUSUM charts are control charts used in the quality control. They are well suited for checking a measuring system in operation for any departure from some target or specified values. In Quality Assurance (QA) of Automate Measuring Systems (AMS). CUSUM charts are used for detecting a drift (of the level) and detecting a change of the precision of the AMS (CEN-EN 14181, 2004). In both cases the CUSUM procedure contains methods for estimating the shift such that maintenance can take place. Agricultural use of CUSUM charts include monitoring pigs based on their drinking behavior (Madsen & Kristensen, 2005) and detecting oestrus in dairy cows (de Vries & Conlin, 2003). Also neural network based expert systems have been developed for animal science applications (Fernández, Soria, Martín, & Serrano, 2006).

This paper focuses on the use of CUSUM charts to detect changes in the measured weight data and the possibilities to use the method in quantifying the duration and seriousness of the problem. The aim of the article is to present the method and evaluate its usage in automated lameness detection.

2. The basic theory of CUSUM charts

CUSUM charts are control charts used in the quality control. They are well suited for checking a measuring system in operation for any departure from some target or specified values. CUSUM charts are based on the statistical theory for sequential tests.

At the ordinary sequential test we consider a sequence of independent random variables $X_1, X_2, \ldots, X_n, \ldots$ and we want to test $H_0 : X_i$ has the density $f(x_i; \theta_0)$ against $H_1 : X_i$ has the density $f(x_i; \theta_1)$.

Given the first j observations $x_1, x_2, \ldots, x_j$ the likelihood functions are

$$L(\theta_0) = \prod_{i=1}^{j} f(x_i; \theta_0) \tag{1}$$

$$\text{and} \quad L(\theta_1) = \prod_{i=1}^{j} f(x_i; \theta_1) \tag{2}$$

The likelihood ratio test is given by

$$\lambda_j(x_1, x_2, \ldots, x_j) = \frac{L(\theta_1)}{L(\theta_0)} = \prod_{i=1}^{j} \frac{f(x_i; \theta_1)}{f(x_i; \theta_0)} \tag{3}$$

Hence, small values of λ_j indicates that H_0 is true, and visa versa.

Given the real numbers A and B ($A < B$), the following rule is introduced to test H_0 against H_1 in a sequential procedure:

(1) $\lambda_j \leqslant A \Rightarrow H_0$ is accepted.
(2) $\lambda_j \geqslant B \Rightarrow H_0$ is rejected.
(3) $A < \lambda_j < B \Rightarrow$ –means that we are still not able to distinguish between the distributions with a reasonable likelihood, and therefore another X is picked up. Using (3) the likelihood ratio is updated using the new observation x_{j+1}, and again the value of λ is evaluated.

In practice it is often more convenient to use the logarithm of λ_j. Hence (3) is written

$$\log \lambda_j = \sum_{i=1}^{j} \log \frac{f(x_i; \theta_1)}{f(x_i; \theta_0)} \tag{4}$$

By introducing

$$z_i = \log \frac{f(x_i; \theta_1)}{f(x_i; \theta_0)} \tag{5}$$

then (4) are written

$$\log \lambda_j = z_1 + z_2 + \cdots + z_j \tag{6}$$

and the above criteria for taking another sample becomes

$$\log A < \log \lambda_j < \log B \tag{7}$$

2.1. Values for the limits

Let us introduce α as the probability for rejecting H_0 given it is true, and β as the probability for accepting H_0, given H_1 is true. Then the following relations between A, B, α and β exist

$$1 - \beta \geqslant B\alpha \tag{8}$$

$$\text{and} \quad \beta \leqslant (1 - \alpha)A \tag{9}$$

Replacing the inequalities above with equalities leads to the Wald approximations

$$1 - \beta = B \cdot \alpha \tag{10}$$

$$\beta = (1 - \alpha) \cdot A \tag{11}$$

In the approximation the exceedence of the limits are neglected. Hence the approximation is best for long runs, i.e. when A and B are large, which they are for small values of α and β.

The formulas above are the basis for constructing the limits used in CUSUM control charts.

3. Towards the CUSUM chart

3.1. The cumulated sum and the V-mask

By considering the logarithm of λ the criteria for continuation for a number of distribution functions can be written on the form

$$l + j \cdot k < \sum_{i=1}^{j} x_i < h + j \cdot k \tag{12}$$

where x is the difference between the sample and the target value, l, h and k for given values of θ_1, θ_2, A and B are constants. This will be illustrated in a later section.

It is now seen that the criteria for taking a new measurement becomes the area between two parallel lines in a plot of the cumulated sum

$$C_j = \sum_{i=1}^{j} x_i \tag{13}$$

against the sample number j. This is illustrated in Fig. 1.

If we simultaneously what to test against some value θ_2, where

$$\theta_2 < \theta_0 < \theta_1 \tag{14}$$

then the two-sided sequential ratio test is obtained (Fig. 2).

In process control the accept criterion is irrelevant, since we want a signal only when the process is out of control. Hence, only the reject area is relevant.

The CUSUM chart corresponds to the sequential ratio test where the reject limits, which are called the V-mask, is reversed such that the origin is placed in the most resent observation. This corresponds to plotting the observations in a reversed sequence as illustrated in Fig. 3.

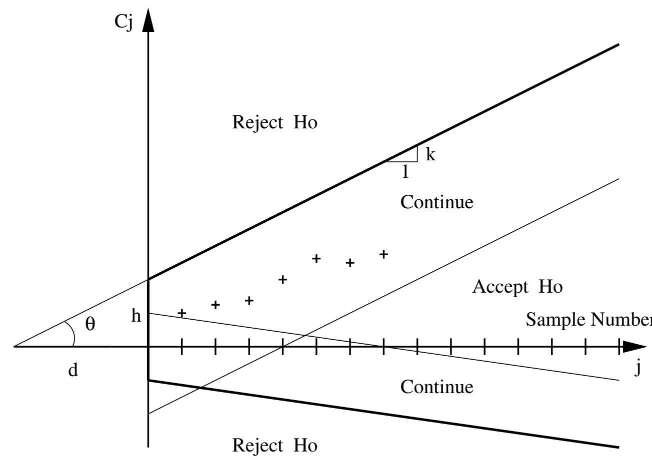

Fig. 2. Two-sided sequential ratio test.

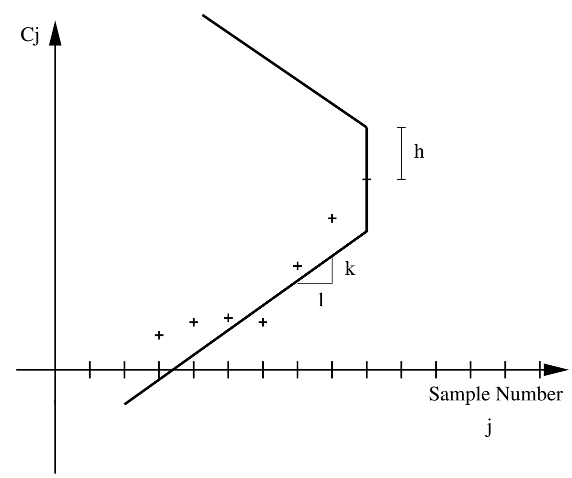

Fig. 3. CUSUM control chart.

3.2. CUSUM $\overline{X}$-chart

CUSUM $\overline{X}$-charts are used for detecting a drift (of the level) of a measurement system. The CUSUM procedure also contains methods for estimating the amount of drift objectively.

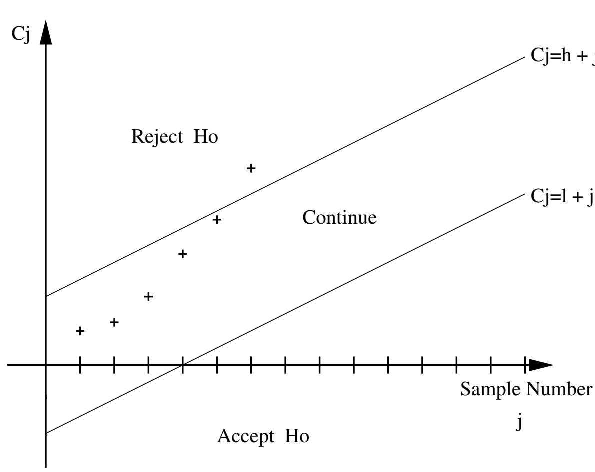

Fig. 1. The principle of the sequential ratio test.

Let us assume that $X_i \in N(\mu, \sigma^2)$, $i = 1, \ldots, j, \ldots$ and σ^2 is known. We want to test $H_0 : \mu = \mu_0$ against $H_1 : \mu = \mu_1$

Using (3) we obtain

$$z_i = \log \left[\frac{\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_i-\mu_1)^2}{2\sigma^2}\right)}{\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x_i-\mu_0)^2}{2\sigma^2}\right)} \right]$$
$$= -\frac{1}{2\sigma^2}(-2x_1(\mu_1 - \mu_0) + (\mu_1^2 - \mu_0^2))$$

The logarithm of the sequential likelihood ratio is (see (6))

$$\log \lambda_j = \left[\frac{j}{2}(\mu_0^2 - \mu_1^2) + (\mu_1 - \mu_0) \sum_{i=1}^{j} x_i \right] \bigg/ \sigma^2$$

and the criteria for taking another measurement is obtained using (7) (($\mu_1 > \mu_0$))

$$\frac{\sigma^2 \log A}{\mu_1 - \mu_0} + \frac{j}{2}(\mu_0 + \mu_1) < \sum_{i=1}^{j} x_i < \frac{\sigma^2 \log B}{\mu_1 - \mu_0} + \frac{j}{2}(\mu_0 + \mu_1) \tag{15}$$

For the CUSUM chart we are interested in the reject area only, hence we write

$$\sum_{i=1}^{j}(x_i - \mu_0) < \frac{\sigma^2 \log B}{\mu_1 - \mu_0} + \frac{j}{2}(\mu_1 - \mu_0) \tag{16}$$

The parameters h and k for the V-mask of CUSUM-$\overline{X}$ chart (Fig. 3) then become

$$h = \frac{\sigma^2 \log B}{\mu_1 - \mu_0} \tag{17}$$

$$k = \frac{\mu_1 - \mu_0}{2} \tag{18}$$

where B is found using (10).

We can normalize the parameters by introducing:

$$h^* = h/\sigma$$

$$k^* = k/\sigma$$

3.3. Onesided CUSUM $\overline{X}$-chart

Onesided CUSUM charts are called alternative or computational CUSUM charts. They detect the drift in exactly same point as traditional charts, but their graphical representation is different. Onesided CUSUM charts are well suited for programming and they have fixed limits shown on the chart. The drawback of the onesided charts is that for two sided schemes two charts operating simultaneously are needed: one for the upper and other for the lower limit.

For the ordinary CUSUM chart we plot the cumulated sum against the sample number j

$$C_j = \sum_{i=1}^{j} x_i \tag{19}$$

where x is the difference between the sample and the target value. This implies that the control limits (i.e. the V-mask) must be moved for each new sample.

If we conclude that the process is out of control, then the following inequality must be satisfied:

$$\exists r: C_n - C_{n-r} \geqslant h + k(n - (n - r))$$

$$\exists r: \sum_{i=1}^{n} x_i - \sum_{i=1}^{n-r} x_i \geqslant h + k \cdot r$$

$$\exists r: \sum_{i=n-r+1}^{n} (x_i - k) \geqslant h$$

where $k(=k^* \cdot \sigma)$ and $h(=h^* \cdot \sigma)$ are limits for the chart selected to obtain the required performance as described in the next section.

It is now clearly seen that for onesided CUSUM charts we can define for values greater than the target:

$$S_j^H = \max[0, x_j - k + S_{j-1}^H] \tag{20}$$

$$S_0^H = 0 \tag{21}$$

and for values lesser than the target:

$$S_j^L = \min[0, x_j + k + S_{j-1}^L] \tag{22}$$

$$S_0^L = 0 \tag{23}$$

and if $S_j^H \geqslant h$ or $S_j^L \leqslant h$ then we reject the hypothesis H_0 that the measuring system is in control. This implies that most likely a drift of the measuring system has occurred.

In summary: We plot the accumulated $\sum(x_i - k)$ as long as the sum is positive. When the accumulated sum becomes negative we put it equal to zero, and if $\sum(x_i - k) \geqslant h$, then the process is out of control and similarly for the lower limit. The procedure is illustrated in Fig. 4.

3.4. The design and performance of CUSUM charts

The performance of the CUSUM-$\overline{X}$ control chart is determined by normalized parameters (h^*, k^*) and measured by the ARL(δ)-function, which is the average number of samples which has to be taken before an "out of control" signal is obtained given that the true bias is δ. The average number of samples is also called the Average Run Length (ARL).

The values (h^*, k^*) are selected such that the CUSUM-$\overline{X}$ chart has a reasonable performance. An optimal CUSUM chart is one which detect a shift of the size $\delta^*(= \delta/\sigma)$ as quickly as possible, while keeping the number of "false alarms" as low as possible. That is ARL(δ^*) is minimized while keeping ARL(δ) at a constant (high) value. The value of ARL(δ) indicates the number of samples between false alarms.

The optimal values for h^*, k^* for given δ and desired ARL were considered and solved by Bowker and Lieberman (1972). Values for one-sided control chart are given in Table 1.

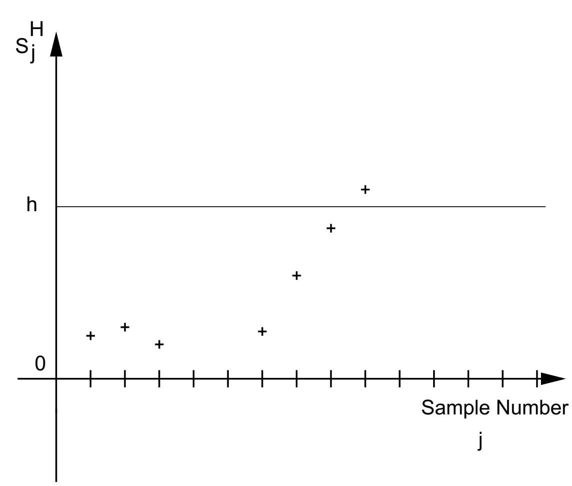

Fig. 4. The alternative onesided CUSUM chart.

Table 1
Design values for the one-sided CUSUM-$\overline{X}$ chart

δ_x^*		ARL(δ)					
		100	200	400	600	800	1000
0.25	k^*	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
	h^*	5.9354	7.8412	9.9977	11.356	12.357	13.150
	ARL(δ^*)	30.238	43.429	59.278	69.582	77.274	83.427
0.50	k^*	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
	h^*	4.4182	5.5974	6.8516	7.6103	8.1571	8.5851
	ARL(δ^*)	14.845	19.343	24.233	27.222	29.385	31.083
0.75	k^*	0.3750	0.3750	0.3750	0.3750	0.3750	0.3750
	h^*	3.4852	4.3281	5.2028	5.7245	6.0979	6.3889
	ARL(δ^*)	8.9859	11.182	13.487	14.868	15.859	16.632
1.00	k^*	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
	h^*	2.8494	3.5020	4.1713	4.5677	4.8506	5.0707
	ARL(δ^*)	6.1078	7.3950	8.7240	9.5137	10.078	10.517
1.50	k^*	0.7500	0.7500	0.7500	0.7500	0.7500	0.7500
	h^*	2.0369	2.4810	2.9332	3.2003	3.3906	3.5384
	ARL(δ^*)	3.4426	4.0376	4.6406	4.9959	5.2489	5.4456
2.00	k^*	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	h^*	1.5316	1.8738	2.2137	2.4129	2.5547	2.6651
	ARL(δ^*)	2.2672	2.6099	2.9560	3.1585	3.3020	3.4132

3.5. Estimation of the drift

Let us define

$$N_j^H = N_{j-1}^H + 1 \quad \text{if } S_j^H > 0 \tag{24}$$

$$N_j^H = 0 \text{ otherwise} \tag{25}$$

$$N_0^H = 0 \tag{26}$$

The quantity N_j^H simply counts the number of samples since S_j^H were 0. N_j^L is defined analogously.

In the case of the ''out of control'' signal the drift is estimated using

$$\delta = f_M(k + S_j^H/N_j^H) \quad \text{for } S_j^H \geqslant h \tag{27}$$

or

$$\delta = -f_M(k + S_j^L/N_j^L) \text{ for } S_j^L \leqslant h \tag{28}$$

The factor f_M is less than one (e.g. $f_M = 0.7$), and is introduced to account for the fact that the estimate of the drift would otherwise be biased towards too high values.

4. Measurements

Four balances were installed into the floor of a milking robot in order to measure the weight on each leg of a cow during milking. Each balance consisted of a balance platform and a single point load cell. The sensors were connected to a four channel carrier frequency amplifier (Spider8, HBM, Darmstadt, Germany) and the data was transferred to a personal computer (PC). The Internet was used for remote control of the system and tracking of the measurements. The measuring frequency was set at 10 Hz (Pastell et al., 2006).

The cows visited the milking robot voluntarily and they wore transponders which are used to identify the cow as usual in such a system. When the cow entered the robot she was milked automatically if enough time had elapsed from the last visit. The cows visited the milking robot voluntarily from 2 to 4 times daily and typical duration of a milking was 5–10 min, depending on the milk yield and flow. The floor of the milking robot used in the experiment is shown in Fig. 5.

Measurement software was made with TestPoint software (Capitol Equipment, Middleboro, MA, USA). The starting and stopping of the measurements was based on

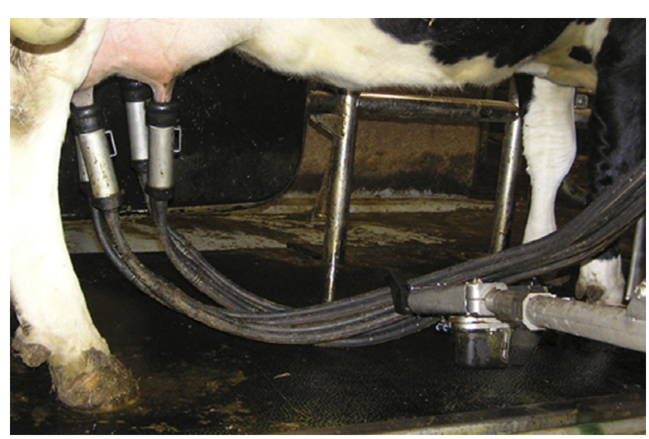

Fig. 5. The floor of the milking robot used in the experiment. The balances are located under the rubber carpet.

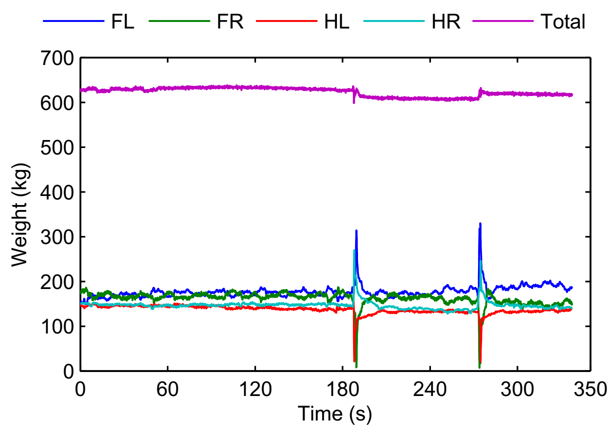

Fig. 6. The leg weights and the total weight of a sound cow during milking. FL = Front left; FR = Front right; HL = Hind left; HR = Hind right; Total = Total weight.

information obtained from a log file created by a program provided by the robots manufacturer DeLaval (Tumba, Sweden). Weight on each leg of a cow was recorded during milking. Measurement was started when the robot started milking a cow and ended when the milking stopped. The data file from every weighing was saved on the computer (Pastell et al., 2006).

Not all of the measurements were successful mainly due to cows standing beside the platforms. This cannot be avoided because of the varying size of the cows; young and small cows proved to be especially problematic. When a cow was not standing directly on the balances it resulted in erroneous values, which were seen as drop in the measured total weight, and were removed from the data. MATLAB was used for removing erroneous values from the data with a special algorithm described in Pastell et al. (2007).

After removing erroneous values from the data the average weight of each leg, the standard deviation of the weight of each leg, and the total body weight of the cow was calculated. Raw data from a measurement is shown in Fig. 6.

All cows were observed weekly for lameness during a normal gait by experienced personnel and lame cows were further checked with clinical inspection in order to find the cause of the problem (Pastell & Kujala, 2007).

5. Application of CUSUM charts to detect lameness

5.1. Constructing the charts

This study focused on the use of onesided computational CUSUM $\overline{X}$-charts for detecting lameness in dairy cows based on the measured leg weight data. We chose to use onesided charts to detect drift in the leg weight data because they are well suited for programming and easier to understand for the end user because the chart shows fixed limits instead of a moving V-mask.

Charts for detecting the drift in the weight of individual limbs and the total weight of the cow were designed. All of the lameness cases identified during the study were in the hind limbs. In order to detect the change in the weight distribution between the parallel legs a leg load index (LLI) for the left hind leg was calculated. It was hypothesized that problems in the left hind leg can be seen as decrease in the LLI and problems in the right hind leg as an increase in the LLI. The need to use a transformation was checked by using a range-mean plot (Madsen, 2006). It was discovered that no transformation was needed and the untransformed data was used. The data was smoothed using first order exponential smoothing (Madsen, 2006) calculated using (30) with forgetting factor $\lambda = 0.9$.

$$\mathrm{LLI} = \frac{\text{weight of the left hind leg(kg)}}{\text{total weight of the hind legs(kg)}} \cdot 100\% \tag{29}$$

$$S_n = (1-\lambda)Y_n + \lambda S_{n-1} \tag{30}$$

where n is sample number, S_n is the smoothed value, Y_n is the observed value and λ is the forgetting factor.

It is shown in Madsen (2006) that S_n corresponds to an adaptive estimation of the mean of Y.

Charts for detecting drift in higher and lower values were used for smoothed LLI (%), smoothed weight of the left hind leg (kg), and a chart for detecting lower values for the smoothed total weight (kg).

We decided that individual values for limits are needed for each cow since they behave in an individual manner. Therefore we chose to use the historical data from each cow to calculate individual target value μ_0 and standard deviation σ for the process. The parameters were then updated for each new sample. Different values of h^*, k^* were evaluated to find suitable performance for the application based on Table 1.

The target value μ_0 and standard deviation σ were computed for each sample number j of each cow and chart from the historical values as follows:

$$\mu_0 = \frac{1}{n}\sum_{i=l}^{m} x_i \tag{31}$$

$$\sigma = \sqrt{\frac{1}{k}\sum_{i=h}^{m}(x_i - \bar{x})^2} \tag{32}$$

where

if $j \leqslant 20$, $n = 10$, $m = 10$, $l = 1$, $k = 10$, $h = 1$
if $j > 20$ and $j \leqslant 40$, $n = j - 10$, $m = j - 10$, $k = j - 10$, $l = 1$, $h = 1$
if $j > 40$ and $j \leqslant 120$, $n = 20$, $m = j - 20$, $l = j - 40$, $k = j - 20$, $h = 1$
if $j > 120$, $n = 20$, $m = j - 20$, $l = j - 40$, $k = 100$, $h = j - 120$

A separate scheme is needed for the beginning of the chart to detect problems early on in the process but the best performance is obviously achieved after $j > 40$, because only then enough historical data has been collected to calculate the target value accurately.

It is also notable that the standard deviation σ is after the first 40 samples calculated from a longer time period than the target value μ_0. This is because the standard deviation is more sensitivity to outliers than the mean. Minimum allowed σ was defined for smoothed LLI as $\sigma = \max[4, \sigma]$ and for smoothed total weight as $\sigma = \max[20, \sigma]$ so that the test would not be too sensitive to small changes, which are normal for all cows.

In a practical application 40 samples means 10–20 days of measurements, depending on how often the cow visits the robot and how many of the measurements are successful. It is a reasonable time period because cows are typically milked with the robot for over 300 days before moved away to calve. Furthermore the cattle tender should know that the cows are not lame when moved to the milking robot.

5.2. Results

Onesided CUSUM charts of S_j^L ($h^* = 2.5$, $k^* = 0.75$) of the smoothed LLI of two cows who became lame during the measurements are shown in Figs 7a and 8a. The LLI, smoothed LLI, the target value μ_0, and, the standard deviation σ used constructing the charts are shown in Figs. 7b and 8b. The lameness has started for both cows around the time when the S_j^L begins to drift.

The cow in Fig. 8 becoming lame also caused a drop in the total body weight of the animal, which was also detected with the CUSUM chart for body weight. The CUSUM chart ($h^* = 2.5$, $k^* = 0.75$) for lower values of the smoothed body weight is shown in Fig. 9. Lameness affects the total weight of animal especially in loose housing systems where animals have to walk to get feed and water and naturally while lame are less inclined to do so. In this case the beginning of lameness was seen almost at the same time point in the CUSUM charts for LLI (Fig. 8) and the total weight (Fig. 9).

CUSUM charts also provide means for detecting the time point when the drift has begun and calculating the amount of drift. This is also very important in lameness research when the duration of e.g. hoof problems are estimated and the severity of different ailments are compared. So far no objective method for this purpose has been available.

The duration and the amount of drift in Fig. 9a was calculated using (25) and (28). At the end of the drift $N_j^L = 17$, $S_j^L = -37.6$, and, $k = 1.88$. Using (28) the amount of drift was calculated as $\delta = -0.7(1.88 - 37.6/17) = 2.86$. The measures (N_j^L, δ) can be used when comparing different lameness cases because they describe the deviation from the cow's own normal status. When comparing different cases the same values of h^* and k^* have to be used.

The effect of k^* with $h^* = 3$ in the performance of CUSUM charts of smoothed LLI of a lame cow are shown in Fig. 10 and a sound cow in Fig. 11. The figures show that with small k^* the charts are more sensitive in detecting drift in the data, but using too small value also can result in false alarms. The lameness case in Fig. 10 was detected with $k^* \geqslant 0.25$, but $k^* \leqslant 0.5$ also caused a false alarm for the cow in Fig. 11. With smaller values the detection of the actual lameness case also occurred sooner. If only these two cases were used to choose the proper k^*, then value of 0.75 would be used.

However choosing the optimal value depends on the desired sensitivity in the actual application, i.e. how mild cases of lameness the user wants to detect and what is the consequence of a false alarm.

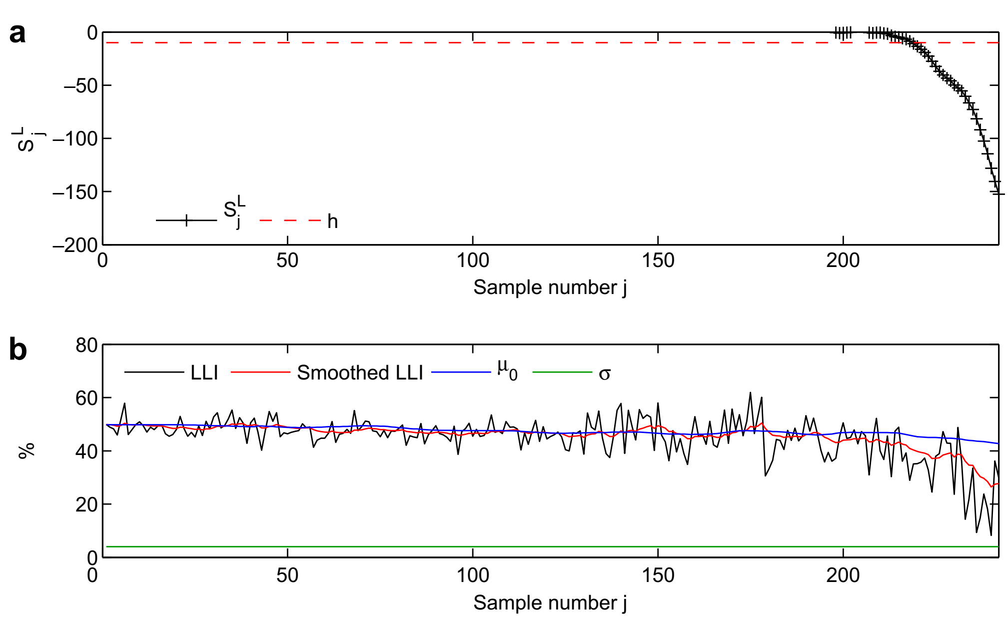

Fig. 7. (a) Onesided CUSUM chart of the smoothed LLI of a cow who became lame during the study and (b) LLI, smoothed LLI, target value μ_0, and σ used for constructing the chart.

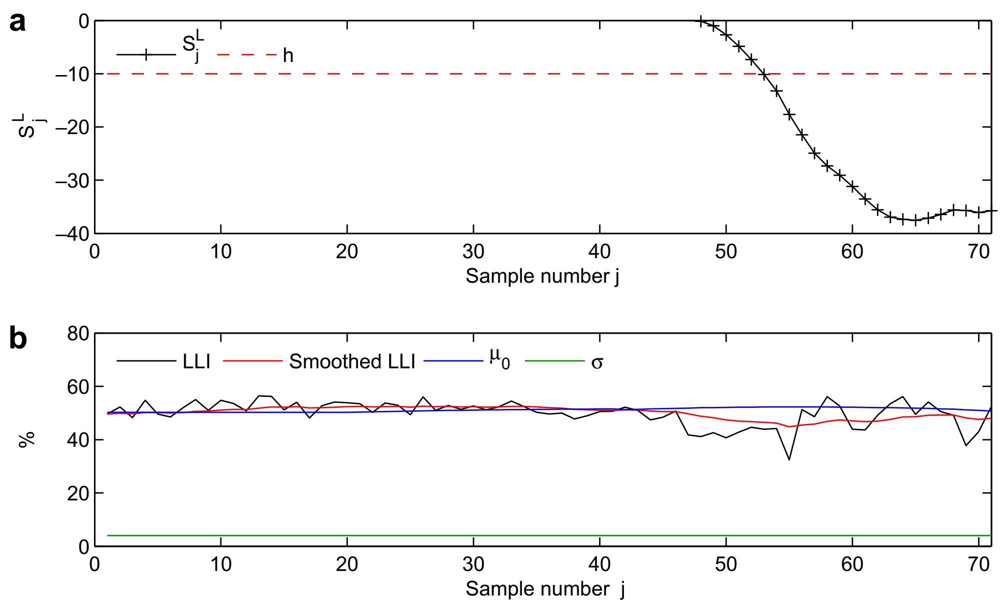

Fig. 8. (a) Onesided CUSUM chart of smoothed LLI of a cow who became lame during the study and (b) LLI, smoothed LLI, target value μ_0, and σ used for constructing the chart.

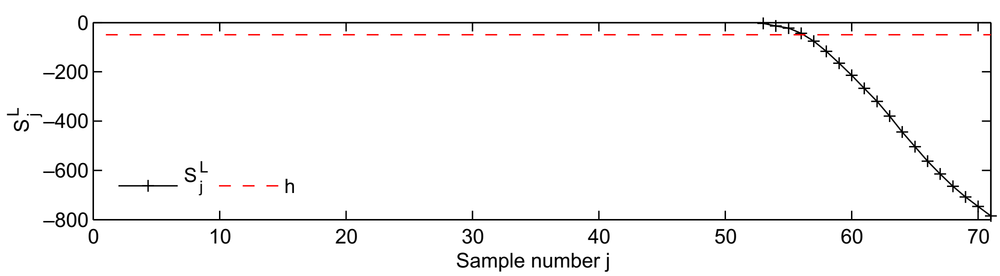

Fig. 9. Onesided CUSUM chart of smoothed total weight a cow who became lame.

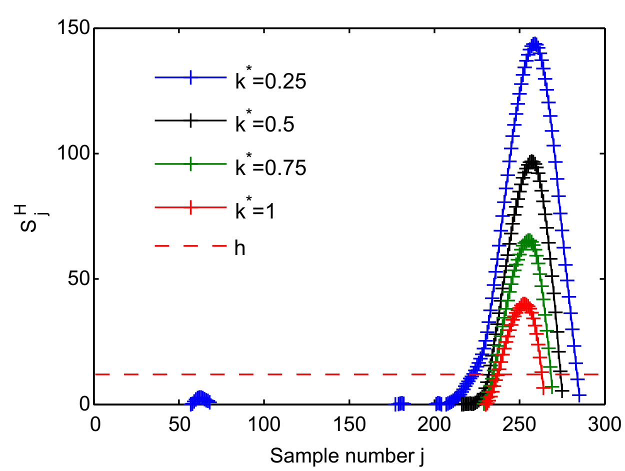

Fig. 10. S_j^H of smoothed LLI of a lame cow with different k^* values.

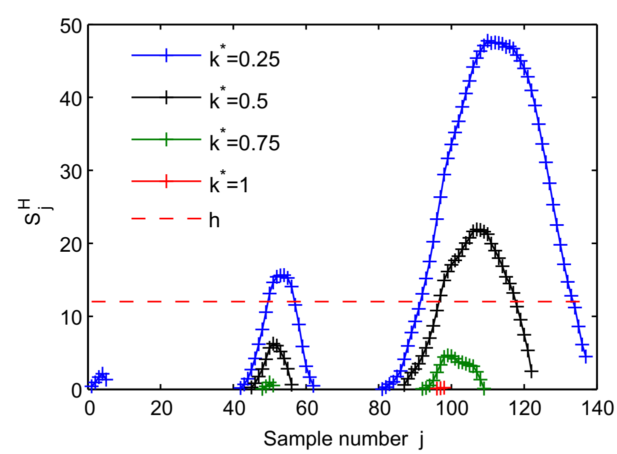

Fig. 11. S_j^H of smoothed LLI of a sound cow with different k^* values.

6. Discussion and conclusions

We have successfully suggested onesided CUSUM $\overline{X}$-charts for detecting lameness based on the leg weights during automatic milking. The target values are calculated using historical data of each cows so the each animal has an individual chart. This makes it possible to objectively monitor the leg health of the animal.

The results are in agreement with what has been previously suggested by Pastell et al. (2006), Pastell et al. (2007) and Pastell and Kujala (2007). Neveux, Weary, Rushen, von Keyserlingk, and de Passille (2006) Rushen, Pombourcq, and Passille (2007) have also shown that leg problems cause changes in the weight distribution of the cow when standing still. Neither (Neveux et al., 2006) or (Rushen et al., 2007) however report timeseries of the measurements. Rajkondawar et al. (2006) have developed a walktrough system with force sensors for measuring lameness from cow's gait and they have also developed logistic regression based models for lameness detection. Their system however may not be suitable for farms with milking robots because they often lack suitable place for gait measurements. Some studies (Magee & Boyle, 2002; Flower, Sanderson, & Weary, 2005) also suggest that image analysis could be a solution for measuring lameness.

We have shown that lameness can be seen as drift in the leg weight data and the amount of drift and its duration can be calculated. This is very valuable information in veterinary research because it provides means for assessing the severity and impact of different causes of lameness and also evaluating the effect of treatment and medication. So far no objective method for calculating these measures has been available and the methodology presented in this paper seems like a very promising possibility for the task. Of course the performance of the system has to be further validated.

The performance of the CUSUM charts in terms of detection rate and number of false alarms can be adjusted by selecting appropriate (h^*, k^*)-values. We do not recommend any optimal values, because the appropriate choice depends on the application and the consequences of missed problems and false alarms. If the system is used in veterinary research then higher sensitivity for detecting problems is probably wanted than for on-farm applications.

There were also some cows that cause alarms with the charts without a known reason. In this study we only inspected the cows for lameness so we do not know if the drift is caused by e.g. hoof diseases which do not cause lameness. Therefore more veterinary research is needed to determine the accuracy of the system as diagnostics test for lameness and hoof diseases.

Lameness is one of the biggest welfare and economic issues in modern dairy production and its impact can be greatly reduced if the problem is detected and treated on time. Furthermore it has been suggested that farmers fail to recognize 75% of the cases (Whay et al., 2003). Automatic early detection of the problem can thus help to improve the economic result of farms and the welfare of animals.

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