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Automatic Lameness Detection in a Milking Robot:

Instrumentation, measurement software, algorithms for data analysis and a neural network model

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ACADEMIC DISSERTATION

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Abstract

The aim of this thesis is to develop a fully automatic lameness detection system that operates in a milking robot. The instrumentation, measurement software, algorithms for data analysis and a neural network model for lameness detection were developed.

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

Increase in automation is a consequence of increasing farm sizes, the demand for more efficient production and the growth of labour costs. As the level of automation increases, the time that the cattle keeper uses for monitoring animals often decreases. This has created a need for systems for automatically monitoring the health of 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 the modern dairy industry. Limb disorders cause serious welfare, health and economic problems especially in loose housing of cattle. Lameness causes losses in milk production and leads to early culling of animals. These costs could be reduced with early identification and treatment.

At present, only a few methods for automatically detecting lameness have been developed, and the most common methods used for lameness detection and assessment are various visual locomotion scoring systems. The problem with locomotion scoring is that it needs experience to be conducted properly, it is labour intensive as an on-farm method and the results are subjective.

A four balance system for measuring the leg load distribution of dairy cows during milking in order to detect lameness was developed and set up in the University of Helsinki Research farm Suitia. The leg weights of 73 cows were successfully recorded during almost 10,000 robotic milkings over a period of 5 months. The cows were locomotion scored weekly, and the lame cows were inspected clinically for hoof lesions. Unsuccessful measurements, caused by cows standing outside the balances, were removed from the data with a special algorithm, and the mean leg loads and the number of kicks during milking was calculated.

In order to develop an intelligent system to automatically detect lameness cases, a model was needed. A probabilistic neural network (**PNN**) classifier model was chosen for the task. The data was divided in two parts and 5,074 measurements from 37 cows were used to train the model. The operation of the model was evaluated for its ability to detect lameness in the validating dataset, which had 4,868 measurements from 36 cows. The model was able to classify 96% of the measurements correctly as sound or lame cows, and 100% of the lameness cases in the validation data were identified. The number of measurements causing false alarms was 1.1%. The developed model has the potential to be used for on-farm decision support and can be used in a real-time lameness monitoring system.

Foreword

Special thanks to my supervisors professor Jukka Ahokas and docent Mikko Hautala for getting me involved and interested in research work. I am grateful for all of the good advice, constructive critisism, patience and numerous interesting discussions regarding this work and science in general.

Many thanks for my co-researcher Minna Kujala for conducting the veterinary part of the study and answering all of my lameness questions as well as helping me to understand the veterinary way of thinking.

I acknowledge the staff of Suitia research farm for their contribution in the experiments and maintenance of the measurement system. This study would not have been possible without your help, coffee and good humour.

Warm thanks to all of my co-authors for their valuable input in the original publications. Especially to docent Väino Poikalainen for presenting original research ideas and sharing his long experience in the field of measuring animal welfare.

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I have had the priviledge to get to know and work with several colleagues who I appreacite greatly. So thank you all of you for commenting my work, presenting your ideas, sharing your experiences and many interesting and fun moments as well as listening and helping in more difficult times.

Thanks also for my parents for supporting me during my studies and introducing me with cows and agriculture already in my early years and for my 2 brothers and a sister for not letting me take myself too seriously.

Most of all I want to thank my beloved wife Helena who has inspired me with her own example, supported me troughout this study and contributed the cover artwork. Thank you for believing in my work and my abilities when I have not.

Contents

List of Original Publications

This thesis is based on the following publications:

I Pastell, M., Takko, H., Grohn, H., Hautala, M., Poikalainen, V., Praks, J., Veermae, I., Kujala, M. & Ahokas, J. 2006. Assessing Cows' Welfare: weighing the Cow in a Milking Robot. Biosystems Engineering, 93(1):81-87.

II Pastell, M., Hautala, M., Poikalainen, V., Praks, J., Veermae, I., Kujala, M. & Ahokas, J. Automatic Observation of Cow Leg Health Using Load Sensors. Computers and Electronics in Agriculture, In press.

III Pastell, M., Aisla, A.M., Hautala, M., Poikalainen, V., Praks, J., Veermae, I. & Ahokas, J. 2006. Contactless Measurement of Cow Behavior in a Milking Robot. Behavior Research Methods, 38(3):479-483.

IV Pastell, M. & Kujala, M. 2007. A Probabilistic Neural Network Model for Lameness Detection. Journal of Dairy Science, 90:2283-2292.

The publications are referred to in the text by their Roman numerals.

The Author's Contribution in the Original Publications

I Matti Pastell was the corresponding author and was mainly responsible for experimental design. In addition, he performed the measurements, analysed the data and wrote the majority of the publication.

II Matti Pastell was the corresponding author and was mainly responsible for experimental design. He performed the measurements, developed and applied the algorithms used in data analysis and wrote the majority of the publication.

III Matti Pastell was the corresponding author and he was responsible for experimental design. He performed the measurements, developed and applied the algorithms used in data analysis and wrote the majority of the publication.

IV Matti Pastell was the corresponding author and responsible for the technical part of the experimental design. He performed the measurements and developed and validated the neural network model described in the paper. In addition, he interpreted the measurements and the model and wrote the corresponding parts of the publication.

Abbreviations

AMS	Automatic milking system
AUC	Area under the curve
FL	Front left
FR	Front right
HL	Hind left
HR	Hind right
ID	Identification
LS	Locomotion score
LWR	Leg weight ratio (%) between the lighter and heavier hind leg
PNN	Probabilistic neural network
ROC	Receiver operating characteristic

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 of increasing farm sizes, the growth of labour costs, demand for more profit and more efficient production as well as the need for leisure time for the farmers. As the level of automation increases, the time that the cattle keeper uses for monitoring animals decreases. This has created a need for systems for automatically monitoring the health of 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 the modern dairy industry. Limb disorders cause serious welfare, health and economic problems especially in loose housing of cattle (Juarez et al. 2003, Klaas et al. 2003) Lameness causes losses in milk production (Warnick et al. 2001, Green et al. 2002) and leads to early culling of animals (Enting et al. 1997). These costs could be reduced with early identification and treatment (Green et al. 2002).

At present only a few methods for automatically detecting lameness have been developed. Rajkondawar et al. (2002) used two parallel force-plates to measure step forces of cows when they walked over the plates. They concluded that the system could recognise lame animals and identify the affected limbs. They also developed a mathematical scoring system for lameness based on their force-plates system and also further developed a model for lameness detection (Rajkondawar et al. 2006).

Also machine-vision based gait analysis with image processing software (Flower et al. 2005) and re-sampling condensation with hidden Markov models (Magee & Boyle 2002) have been used to detect lameness in dairy cows. One commonly used technological method in commercial production is the utilization of activity meters worn on the leg or around the neck. These systems are mainly designed for heat detection, but they can also help detect decreased activity levels caused by lameness.

Visual inspection with locomotion scoring systems (Manson-Leaver 1988, Sprecher 1997) is still today the most common way to assess lameness. The use of these systems requires expertise, and the systems have been shown to be subjective (Wincler & Willen 2001). Studies also show that farmers are aware of only 25% of lame animals in their herd (Whay et al. 2003).

The gait measurements and locomotion scorings are usually performed when the cows exit the milking parlour. However, barns designed for automatic milking often lack corridors for these types of automated measurements.

The aim of this thesis was to develop a fully automatic lameness measurement system that operates in a milking robot. The instrumentation, measurement software, algorithms for data analysis and a neural network model for lameness detection were developed.

2. Review of the Literature

2.1 Automatic Monitoring of Animals

Loose housing of cows with application of automatic systems has become increasingly popular. The number of automatically milking farms almost doubled between the years 2002 and 2006, from 2200 farms (de Koning & Rodenburg 2003) to around 4000 farms (de Koning 2006).

As automation increases and lessens human contact with animals, the possibility of discovering welfare and health problems decreases. Conventional welfare assessment methods are mostly based on various behavioural observations and tests, clinical health examinations and management databases. Therefore, a need to automate welfare and health control has become apparent. It has been suggested that a combination of data used for health management and selected indicators of animal welfare may be used to track changes in welfare over time (Krebs et al. 2001, O'Callaghan et al. 2003).

New technologies have made it possible to collect an increasing amount of data from animals automatically (Berckmans 2004). Animal husbandry is especially suited for data collection because of the diversity of relevant information that can be collected (Frost et al. 1997). A lot of information about the animals is already collected in today's automated production environment, which suggests that livestock producers are willing to adopt new methods. Integrated monitoring systems have the potential to improve efficiency and quality control as well as enable collecting production history for consumers, thus enhancing traceability.

Several authors have developed methods for health monitoring of animals. These systems are based on either behavioural or physiological measurements. Behavioural monitoring systems include for instance a system for monitoring the condition of piglets based on their drinking behaviour (Madsen et al. 2005, Madsen & Kristensen 2005), a computer vision based system for tracking pigs (Tillet et al. 1997) and an indoor cow tracking system (Huhtala et al. 2007).

Measuring physiological parameters often requires disturbing the animal in some manner but also provides accurate information about the subject, and thus a lot of effort has been put into, the development of appropriate methods. Studies include systems for measuring heart rate of poultry (Kettlewel et al. 1997), dairy cattle (Lefcourt et al. 1999, Kaihilahti et al. 2006, Martinez et al. 2006), monkeys (Deutsch 1975) and rabbits (Kaplan et al. 1968). Also systems and instruments for measuring body temperature of livestock have been developed in numerous studies (Wilhelm 1936, Cotter 1974, Lefcourt et al. 1996;1998;1999, Poikalainen 1999, Kettlewell et al. 1997, Hillman et al. 2005, Martinez et al. 2006). Respiration rate of cattle (Howell & Paice 1989, Eigenberg et al. 2000) and swine (Eigenberg et al. 2002) has been measured to get information about heat stress and workload. The measurement of body weight can be used to get information about the health status of dairy cows (Maltz et al. 1997, Maltz 1997), and a method for weighing cows in motion has also been developed (Cveticanin 2003, Cveticanin & Wendl 2004).

Measuring milk parameters can be used to get information about e.g. udder health and nutrition. A method for automatically measuring intracellular enzyme Lactate Dehydrogenase (Blom & Friggens 2007) and fat and protein content (Halachmi et al. 2006) from during milking have been reported.

Several studies have also addressed the topic of measuring lameness, but these will be discussed in a later chapter.

In order to turn the measured data into useful information, intelligent systems are needed to identify the health problems and changes in behaviour. Some of the successful applications of models in automatic detection of health problems include a fuzzy logic model to detect mastitis based on electrical conductivity, milk production rate and milk flow rate (Cavero et al. 2006), a state space model to monitor the drinking behaviour of young pigs (Madsen et al. 2005) and a probabilistic neural network model to recognize pig cough (Chedad et al. 2001, Moshou et al. 2001).

The milking robot is an especially suitable location for automatic monitoring of dairy cows since the cows visit the robot several times a day and spend several minutes in a confined stall. This provides the oppoturnity for computerized monitoring and control of the animals. The use of sensors to monitor body weight and udder health is not limited to milking robots, but the need to perform automated monitoring is the greatest in automated systems with less human contact (Maltz & Spahr 1997). A smaller amount of sensors are also needed for monitoring tasks, as compared to milking parlours, because cows visit milking robots one at a time. This also reduces the cost of monitoring per animal.

2.2 The Importance of Lameness

2.2.1 Prevalence of Lameness

Multiple studies have been conducted to find out the number of cows suffering from lameness and hoof lesions. Whitaker et al. (1983) reported annual incidence of lameness in the UK to be 25% based on veterinary and farmers records. Clarkson et al. (1996) collected data from lameness reports of the veterinary surgeons hoof trimmers and the farmers. In addition, they locomotion scored the cows for prevalence records. They found 55% annual incidence and 21% prevalence at 37 UK dairy farms, the prevalence varied from 2% to 50% and annual incidence from 11% to 170% between farms. Klaas et al. (2003) discovered 14% prevalence of lameness in 8 AMS herds with over 1300 cows in total in Denmark. Green et al. (2002) studied five farms and over 900 cows in the UK and found lameness incidence of 70% over 18 months. Lameness prevalence has been reported also from many other countries: 25% in Wisconsin, USA (Espejo et al. 2006), 10% in Switzerland (Bielfeldt et al. 2004) and 5% in Sweden (Manske et al. 2002). Manske et al. (2002), however, suspects that the number of prevalence in Sweden may be an underestimate because of suboptimal lameness assessment conditions and possible culling of lame animals before the observations were conducted.

Numbers from different studies conducted in the UK suggest that the incidence of lameness is rising, although there are multiple things that can affect the figures and the studies are not directly comparable. Still all of the studies show that lameness affects a great percentage of cows and new methods for detecting and treating the problem are needed.

Loose housing of cows is becoming more common in Finland and it can lead to increased prevalance of lameness since several authors report leg problems to be more common in loose housing than in tie-stalls (Faye & Lescourret 1989, Hultgren 2001). Bielfedlt et al (2005), however, found in a study comparing tie-stalls with loose housing that the hoof health was best in loose housing systems with regular outdoor exercise, although they also found that white line problems were more common in loose housing than tie-stalls. They also point out that several factors, such as material and moisture of walking surfaces, space and design of resting area; need to be taken into account when comparing different housing systems.

It has been reported that close to 90% of the lameness cases are because of foot lesions (Murray et al. 1996, Vermunt 2004), although all foot lesions do not cause lameness (Manske et al. 2002). The remainder of the cases are associated with limb problems. The majority of the problems are in the hind legs (Andersson & Lundström 1981, Murray et al. 1996, Vermunt 2004).

2.2.2 Economic and Welfare Implications of Lameness

Lameness is a crucial welfare issue in modern dairy production (Vermunt 1992, O'Callaghan et al. 2003, Whay et al. 2003, Rushen et al. 2006). Lame cows suffer discomfort and pain of long duration if the problem remains untreated (Wincler & Willen 2001).

Cattle often mask pain instinctively, which leads to delayed detection and treatment of lameness. Because the cows do not express pain, which is a serious component of lameness, pain medication is often overlooked in treatment of the problem. Assessment of pain is a crucial issue in veterinary and welfare research, but pain is subjective and it is very difficult to measure (Rutherford 2002, O'Callaghan et al. 2003).

Lameness is also an economic problem for farmers. Economic losses are caused by prolonged calving intervals, costs of premature culling, reduced milk yield and quality, and veterinary costs or treatment by the farmer himself (Enting et al. 1997). According to a study conducted by Green et al. (2002), a decrease in milk yield occurred from 4 months before to 5 months after the cow was diagnosed as clinically lame. In their study, the average loss of milk yield due to clinical lameness over 305-day lactation was 360 kg. Others (Rajala-Schultz 1999, Warnick et al. 2001, Hernandez et al. 2002) have also reported loss in milk yield due to lameness. The loss of production and the effect of lameness on cows welfare can be minimized if lameness is detected at an early stage and treatment is started as soon as possible (Green et al. 2002).

A decreased number of voluntary milkings per day has been associated with lameness, which consequently may have a negative effect on feed intake and thus body condition and production. Reduced locomotion is particularly harmful in automatic milking systems also because the throughput of such a system depends on the steady flow of voluntary cow traffic (Spahr & Maltz 1997).

Lameness results in earlier culling of animals (Booth et al. 2004, Sogstad et al. 2007) and also lower carcass weight, conformation class, fat cover class and hence a lower economic value of the carcass (Sogstad et al. 2007). Sogstad et al. (2007) conclude that prevention or early identification and treatment of the problem can improve the value of the carcass and reduce culling rates. Several studies (Collinck et al. 1989, Sprecher et al. 1997, Hernandez et al. 2001, Garbarino et al. 2004) have also shown that lameness has a negative effect on the fertility of dairy cows.

Prevention of lameness before the problem occurs is the most important step in the reducing the negative welfare implications for cows and costs for the farmers. Mill and Ward (1994) stated that farmers with the best knowledge and awareness of lameness have the least lameness problems in their herds. Nordlund et al. (2004) suggested that identifying the prevalence and cause of lameness in a herd is necessary for systematic prevention of the problem. Guidelines for lameness control and prevention and control are given by Vermunt (2004).

2.3 Detecting and Assessing Lameness

2.3.1 Locomotion Scoring Systems

Locomotion scoring is the most common way of assessing lameness in cows, and several modifications to this method have been used in lameness studies (Manson & Leaver 1988, Clarkson et al. 1996, Sprecher et al. 1997, Whay et al. 1997, Wincler and Willen 2001, O’Callaghan et al. 2003, Flower and Weary 2006, Rajkondawar et al. 2006). Two popular systems in use have been developed by Sprecher et al. (1997) and Manson and Leaver (1988). The common principle is that the cow is assigned a score describing the condition of the animal based on posture and stride variables. The scoring scheme can be for instance from 1 to 5 (Sprecher et al. 1997) or a continuous numerical rating scale from 1 to 100 (Flower and Weary 2006).

A common problem in all of the visual scoring systems is that they require experience before the scoring becomes consistent, and they are also observer dependent. Several studies have shown that the results of locomotion scoring are subjective. O’Callaghan et al. (2003) reported that the intra-observer repeatability in gait scoring for the 5 point numerical scoring system was only 56% and the interobserver repeatability was only 37%; however when a one-point difference was allowed, the scores were in agreement for 93% and 81% of the scores, respectively. Winkler and Willen (2001) found 68% repeatability of scores among 3 observers. Flower and Weary (2006) were able to detect 22 of 24 cows with sole ulcer from healthy cows with a 5 point numerical rating system and overall visual score. They also found, however, that apparently healthy cows had an average gait score of 3.1. Winckler and Willen (2001) suggest that the usefulness of locomotion scoring systems is limited to indicators of pain reaction.

2.3.2 Technological Systems

Technological systems have two advantages over visual rating schemes: They are observer independent and can be automated to perform the task. Automatic monitoring systems also enable assessing the condition of an animal over time which has been suggested to reflect the condition of the animal more accurately than measurements that take place only once (O'Callaghan et al. 2003).

Only a few methods for automated lameness detection have been presented so far. A commonly used method is the utilization of activity meters worn around the neck or on the leg. These systems are mainly designed for heat detection but they can also help detecting decreased activity levels caused by lameness (O'Callaghan et al. 2003).

Rajkondawar et al. (2002a; 2002b; 2006) were able to successfully separate sound cows from lame cows with a walkthrough system. The system has two parallel force plates that measure the ground reaction forces of individual limbs. A fuzzy logic algorithm was used to separate the measurements of multiple cows to individual files (Tasch & Rajkondawar 2004). Rajkondawar et al. (2006) also developed gait- and lesion-based logistic regression models to detect lame cows and evaluated the performance of the models with receiver operating characteristic (ROC) curves.

ROC analysis is used to evaluate the accuracy of a model or test in separating positive from negative cases. ROC surve captures the trade-off between sensitivity and specificity over the entire range of a model with continuos values and the results are independent of the prevalence of posivite cases in the study population (Lasko et al. 2005). The discrimination accuracy of a test is described with an area under the curve (AUC). An AUC of 1 represents perfect discrimination and area of 0.5 represents no discrimination (Hanley & McNeil 1982, Lasko et al. 2005).

Rajkondawar et al. got AUC of 0.84 in the best case, which means that the system is considered to be a good test in recognizing lame animals. Their system is now commercially available.

Flower et al. (2006, 2005) used a video recording system with reflective markers in the limbs of cows to analyse stride variables. They were able to identify cows with sole ulcers from sound cows with decreased stride length, slower walking speed, increased stride duration and longer periods of three-legged support. They, however, had to manually digitise the recordings, so the system was not yet ready to be used in automated lameness detection. Flower et al. (2006) also found that the best time to conduct gait measurements is after milking when the differences between lame and sound cows could be seen most clearly.

Neveux et al. (2006) utilised a system that measures leg weight distribution for all four limbs. They found that discomfort under a hoof caused cows to keep less weight on the affected leg and shift weight to the contra lateral leg. Rushen et al. (2006) found that pain medication had an effect on the weight distribution and weight variability. They suggested that weight shifting during standing is a sign of pain. The variability of the weight between legs may be a better indicator than just a leg bearing less weight (Neveux et al. 2006, Rushen et al. 2006).

Van der Tol et al. (2004; 2005) and Carvalho et al. (2005) measured the pressure on different parts of the hoof with pressure sensitive sensors to observe the effects of hoof trimming on the weight balance under the hoof. Neither of them, however, reports use of their system in lameness detection.

3. Aims

The purpose of the study was to develop a system for automatic lameness detection in a milking robot. The focus of this thesis was in developing the instrumentation, measurement software and data analysis. The more specific aims of the study were:

1. Develop the measurement system and software for automatically registering the leg weights during milking (I, II).

2. Develop algorithms for removing erroneous values and analysing the raw data (II).

3. Find out if lame cows can be differentiated from sound cows based on the information acquired with the system (III, IV).

4. Develop and validate a model to automatically detect lameness based on the measured data (IV).

4. Materials and Methods

A four balance system for identifying leg problems in a milking robot was developed (I, II). The individual leg weights of a herd were automatically recorded with the system and the leg health of the cows were followed with locomotion scoring and clinical inspection.

The development of the measurement system began in 2003, but due to technical problems with the durability of the balances, the data collection did not begin until June 2004. The data analysis in this thesis mainly focuses on the measurement period from 15 June to 17 September and 20 October to 7 December 2004. The data between the periods was missed due to technical difficulties.

The study was conducted at the University of Helsinki research farm Suitia in an insulated free-stall barn that had DeLaval (Tumba, Sweden) Voluntary Milking System. There were two milking robots at the farm, but only one was used in the study. The cows were milked in two groups, one for each robot. There were 40-45 cows in the group milked with the robot used in the study during the measurement period. Because the cows were sometimes transferred from one milking group to another, we were able to follow altogether 73 cows with the system.

Algorithms for analysing the raw data and removing erroneous values from the data were developed (I, II, III). The processed data was used to detect lameness and finally a neural network model classifying cows into lame and sound groups based on the measurements was developed (IV).

4.1 The Measurement System

Four balances were installed into the floor of a milking robot after careful inspection of the leg positions of all cows from the experimental group during milking (Hämäläinen 2003). Each balance is constructed from a plywood plate on top of a steel plate that is attached to a strain gauge (1510, Vishay Tedea-Huntleigh, Chatsworth CA, USA) with a capacity of 500 kg. The size of the balances ranges from 310 mm × 310 mm to 390 × 445 mm depending on the location and robot’s chassis structures (Figure 1, Figure 2). The platforms located under the hind legs are a bit larger than the ones under the front legs as it was found that the position of the hind legs during milking tended to vary more than the position of the front legs (I).

Many problems with the durability of the system were encountered during the initial set up. The mountings of the sensors proved not to be durable enough for the application and the fixing had to be reinforced by welding extra support to the floor attachment and the metal plate in the balance platform. With the additional reinforcements the system mechanically endured the data collection period of six months used in the modelling. However, a break of one month in the research period was experienced because of damaged wiring.

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 distance between the balances and the amplifier was 40 m. The level of noise in the system was determined by measuring the standard deviation of a constant load of 180 kg during 120 s, the standard deviation was 0.06 kg. This means that in spite of the long wiring, the level of noise remained low. The Internet was used for remote control of the system and tracking of the measurements. Four web cameras were also installed and video from the milking was recorded and stored digitally on PC. Abnormal behaviour could be seen afterwards from the video data. The measuring frequency was set at 10 Hz in order to record the kicks properly because it was found that the duration of a kick can be as short as 0.5 s (Figure 3).

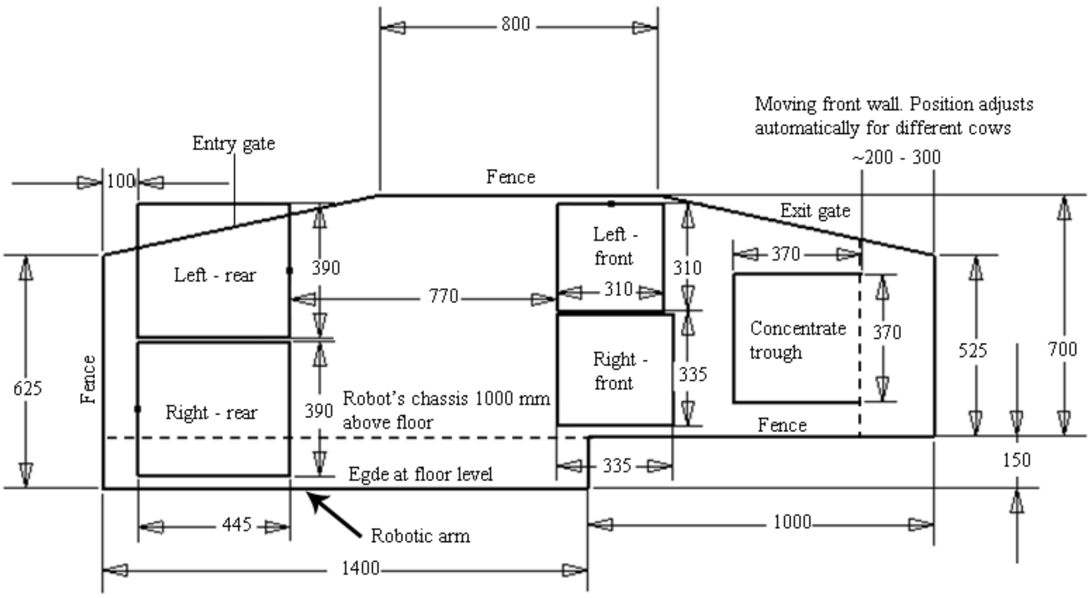

Figure 1 *Dimensions (mm) of the balance platforms and the milking robot. (I)*

The balances were calibrated after the installations and repairs, and the calibration was checked twice during the measurement period of five months. The calibration was performed using 11 weights of 30 kg and one weight of 50 kg. The weights were added on top of the sensor one at a time and the output was measured to determine the linearity and calibration coefficient of the sensors. The effect of the location of the load atop the platform on the measurement result was tested by measuring a load of 130 kg in the corners and then in the centre of the balance. It was found that the output of the sensors is linear and the location of the load had less than a 1 kg effect on the output of the sensor. Checking of the calibration was performed using a load of 180 kg, and it was found that the calibration of the balances had not changed over time. Figure 2 shows the installation of strain gauges in the floor of the robot and the location of the plates on top of the four balances as they are positioned in the robot. An automatic taring system was added to the system in order to minimise the effect of drifting caused by temperature changes. The taring occurred during washing of the robot (3 times daily), and the taring value was saved in a data file. The mean drift per sensor during a 2 week follow up was 2.0 kg with standard error of ±0.4 kg.

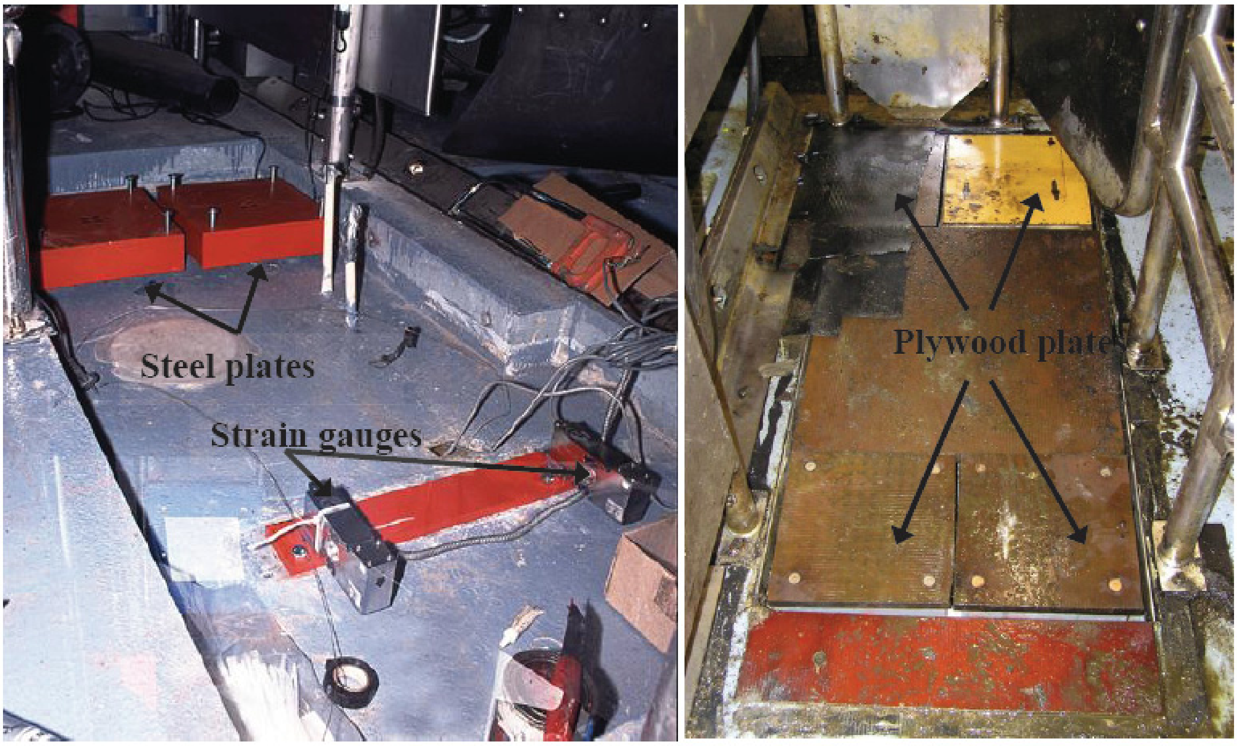

Figure 2 *The strain gauges and the plywood plates on top of the balances as they are positioned in the floor of the milking robot (III).*

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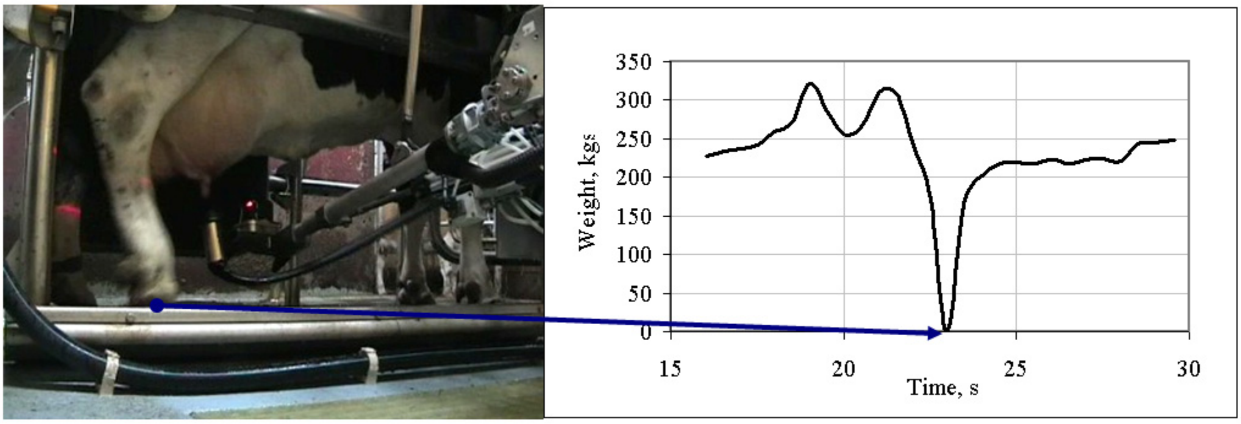

Figure 3 *Weight change of the right hind leg during a kick. (I)*

Measurement software was made with TestPoint software (Capitol Equipment, Middleboro, MA, USA). The starting and stopping of the measurements was based on information obtained from a log file created by a program provided by DeLaval. The log file contained the ID of the cow in the robot and information about the robot's action at each moment. The actions included milking, feeding, washing (the robot) and idling.

The weight on each leg of the cow was recorded during milking. Measurement was started when the robot started milking and ended when the milking stopped. The data file from every weighing was saved on the PC. Mean value, standard deviation and the number of kicks for each leg were calculated automatically after each weighing. The values were then compared to the values previously obtained from the cow in order to find leg problems. Notification of possible problems was displayed if the difference in the average weight of parallel legs was constantly greater than 20%. Cows that gave a notification were then locomotion scored weekly and checked for hoof problems clinically every three weeks.

4.2 Lameness Assessment and Clinical Inspections

All cows were observed by experienced personnel weekly for lameness during normal gait. A locomotion scoring system by Sprecher et al. (1997) was used during the visual inspections (Table 1). The cows that scored at least 2 during the weekly inspections were then inspected clinically for hoof problems during hoof trimming. In addition, all cows that were at risk (2 to 5 months in milk), all primiparous cows, and all cows that showed signs of lameness based on the leg weight measurements were examined clinically every 3 weeks. In total, 16 lameness cases caused by hoof problems in 15 cows and 2 lameness cases in 2 other cows resulting from injuries were observed. All lameness problems detected during the study were in the hind legs. The protocol used in scoring hoof lesions was that used nationally by Finnish hoof trimmers consisting of 9 different lesion scores (Kujala et al., 2004). Haemorrhages, sole ulcers, and white-line problems were scored more accurately and were also described verbally. If a sole was off, it was recorded separately in addition to the problem involved (e.g., bad white-line disease). The protocol used in scoring lesions identified during the study is presented with greater detail in publication IV.

Table 1. *Criteria used to assign a lameness score and clinical description to cattle (Sprecher et al. 1997)*

Lameness Score	Clinical description	Assessment criteria
1	Normal	The cow stands and walks with a level-back posture. Her gait is normal.
2	Mildly lame	The cow stands with a level-back posture but develops an arched-back posture while walking. Her gait remains normal.
3	Moderately lame	An arched-back posture is evident both while standing and walking. Her gait is affected and is best described as short striding with one or more limbs.
4	Lame	An arched-back posture is always evident and gait is best described as one deliberate step at a time. The cow favors one or more limbs/feet.
5	Severely lame	The cow additionally demonstrates an inability or extreme reluctance to bear weight on one or more of her limbs/feet.

4.3 Data Processing

The validity of the acquired data had to be checked before using it in health monitoring. 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 data, which could, however, be differentiated from correct values. MATLAB was used for removing erroneous values from the data (II).

During one milking, the standard deviation of the cow's weight (i.e. the weight change caused by milking) and of noise from the system did not exceed 15 kg when the cow was standing on the balances during the whole weighing. Therefore, erroneous values were removed from all weighings with over 15 kg standard deviation.

The operation of the program used for elimination of erroneous data is shown in Figure 4. Every data file consisted of 6 columns and a variable number of rows depending on the length of the weighing (milking). The columns contain the measurement time, the leg weights and the total weight. Every reading from the balances created a new row in the file. At first the program searched for the maximum weight of the cow during milking and then the total weight of each row in the file was compared to that maximum. We decided that if the difference between the maximum weight (W_{max}) and the total weight on the row (W_n) was over 30 kg, the whole row was removed from the file. The operation was performed automatically for all measurements. If less than 90 s of the original weighing remained after removing erroneous data, the whole weighing was discarded from further analysis (II).

After removing erroneous values from the data the average weight of each leg, the standard deviation of the weight of each leg, the body weight, the number of kicks and steps and the frequency (times/minute) of kicks and steps were calculated for each weighing (=milking). A “kick” was described as lifting of the leg and calculated when the weight of a leg decreased to less than 5 kg (in order to avoid the effect of possible drift in the zero level) and a “step” was described as weight shifting and was calculated when the weight of a leg decreased to between 5 kg and 20 kg (III, IV).

Because all of the leg problems that were identified during this study were in the hind legs, we focused on analysing the weight data from hind legs. In order to handle the leg problems in both hind legs in the same model, a leg weight ratio (**LWR**) between the lighter and heavier hind leg was calculated for each weighing (1).

(1) $$LWR = \frac{Lighter\ hind\ leg}{Heavier\ hind\ leg} \cdot 100\%$$

where LWR = leg weight ratio.

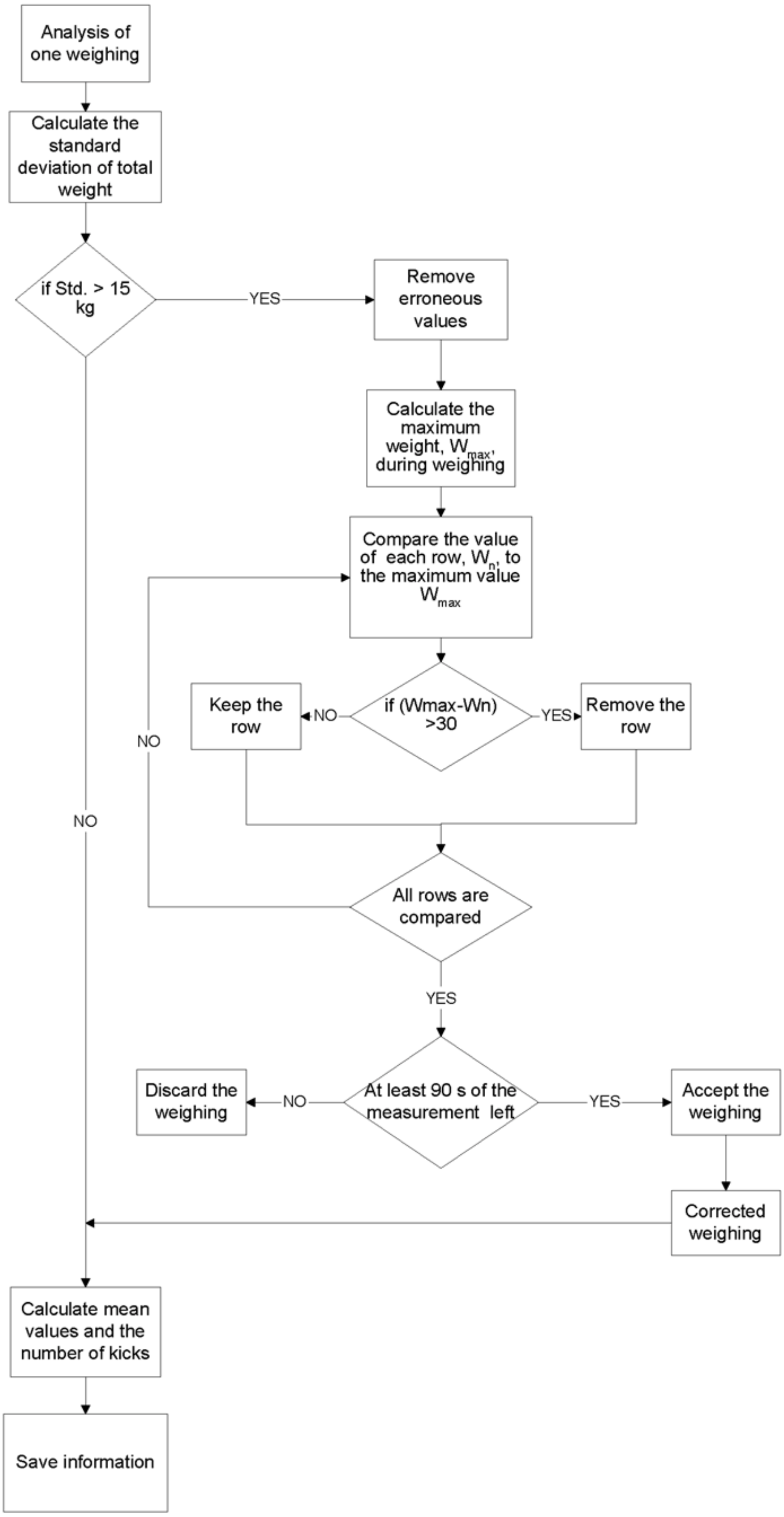

Figure 4 *Flowchart of the program used in removing erroneous values from raw data (II).*

4.4 A Neural Network Model for Lameness Detection

It was soon discovered that the alarm system used in the measurement software, which was triggered if there was more than 20% weight difference between parallel legs, gave too many false alarms (I, II). Therefore a more sophisticated method to classify the cows into lame and sound groups was needed.

Probabilistic neural network (**PNN**) was chosen for the task. PNN is an artificial neural network that is used for data classification tasks (Specht 1988; 1990). The model is relatively easy to implement, its operation is transparent and it can be adapted with a single parameter. The model preserves the whole teaching dataset, so no information is lost in teaching due to data reduction or model fitting. PNN also allowed using the same model for all cows in the data set rather than building an individual model for each cow. The advantage of this approach is that no historical data from an individual animal is required to make a classification. It also meant that we could utilise the data from all cows in the study, regardless of how many milkings we were able to measure from each individual. This would not have been possible with a model requiring a longer time series of data.

The model has also been found to be a powerful classifier in several studies. Applications include pig cough recognition (Chedad et al. 2001), clinical diagnosis of cancer (Shan et al. 2002, Goriness et al. 2005), classification of freeway traffic patterns (Lian Choong et al. 1996, Srinivasan & Ruey Long Cheu 2001), predictive classification of hospital defibrillation outcomes (Yang et al. 2005) and cereal grain classification (Paliwal et al. 2000, Visen et al. 2002).

4.4.1 Probabilistic Neural Network

PNN in the Matlab Neural Network toolbox 4.0 consists of 2 layers: a radial basis layer and a competitive layer. It is notable that the formulas presented here are the ones used in the toolbox functions and differ to some extent from those presented by e.g. Specht (1988; 1990), but the idea in the classification is very similar. The model is first taught with a series of data vectors and their correct classification. When a new input vector is presented, it is classified based on the information found in the teaching data.

Consider the two category situation. The data has two possible classifications, θ_A or θ_B. Both classes are represented by a set of measurements (from the teaching data) forming $i \times j$ dimensional matrix $x_{class}=[x_{11} \ldots x_{nm} \ldots x_{ij}]$, pattern matrixes for θ_A and θ_B are denoted by x_a and x_b.

The value of radial basis layer $f_A(x)$ of class θ_A for new pattern x is calculated as the sum of radial basis functions centered at each training sample as (Demuth & Beale 2000):

(2) $$f_A(x) = \sum_{i=1}^{n} \exp\left[-\frac{0.8326}{\sigma} \sum_{j=1}^{m} (x_j - x_{aij})^2 \right]$$

Similarly, the value of $f_B(x)$ of class θ_B at x:

(3) $$f_B(x) = \sum_{i=1}^{n} \exp\left[-\frac{0.8326}{\sigma} \sum_{j=1}^{m} (x_j - x_{bij})^2 \right]$$

where i = pattern number
x_j = the jth element of new input pattern x
x_{aij} = the jth element in the ith pattern in matrix x_a
x_{bij} = the jth element in the ith pattern in matrix x_b
σ = spread of the network function given as user input
n = number of patterns in the pattern matrix of the respective class

The second competitive layer chooses the class with the largest value according to Bayes decision rule, without a priori knowledge, and assigns vector x to that class (Specht 1988):

(4) $$d(x) = \theta_A \text{ if } f_A(x) > f_B(x)$$

(5) $$d(x) = \theta_B \text{ if } f_B(x) > f_A(x)$$

Spread σ is given to the network as user input to adjust its behaviour. When $\sigma<0.8326$ the patterns x_{ij} closest to x get higher weight and when $\sigma>0.8326$ the patterns in x_{ij} with larger distance from x become also important in the classification. Figure 5 illustrates the effect of σ in the value of radial basis function (6) with different Euclidean distances between x_i and x.

(6) $$\exp\left[-\frac{0.8326}{\sigma} \sum_{j=1}^{n} (x_j - x_{ij})^2 \right]$$

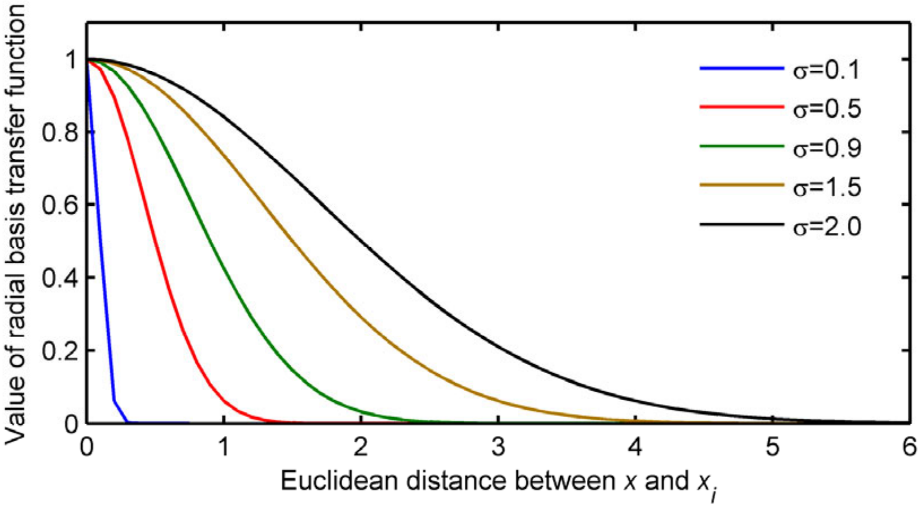

Figure 5 *The effect of spread (σ) on the value of radial basis transfer function with different Euclidean distances between x and* x_i.

4.4.2 Classification of the Data

Each of the measurements in the study was classified either as sound (9,499 measurements from 72 cows) or lame (443 measurements from 17 cows with 18 lameness cases) based on the locomotion scores (LS) and clinical inspections. Measurements were classified as sound when the cow had LS of 1 or 2 and no clinical problems were found. Measurements were classified as lame when LS was at least 3 or serious clinical problems were found. The beginning of the lameness was then assessed from the weight curves as in Figure 6. Arrows in the figure show the time the cow was judged lame according to the curve and the time the actual veterinary diagnosis took place. The cow suffered from lameness because of an injury involving the left hip and had LS of 5.

Help from the curves was needed because lameness was not assessed daily by the observers. This also meant that the beginning of lameness in the data was not necessarily the same as the beginning of clinical lameness, because we cannot be sure when exactly the clinical lameness started.

We were able to assess measurements from 16 of 17 lame cows during a period when they were not lame. Therefore, measurements from those 16 cows exist in both data sets (sound and lame) resulting in a total of 73 cows (Table 2).

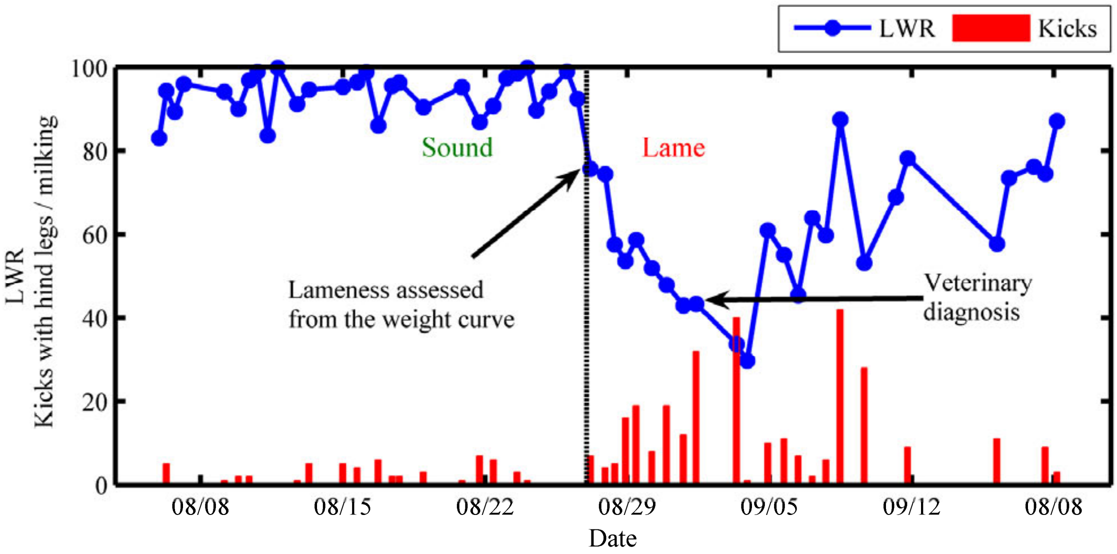

Figure 6 *Lameness classification assessed from the weight curve. On the left panel the cow has been classified as sound and on the right panel as lame.*

Furthermore, the data set was divided into 2 groups with data from different cows for model development and validation (Table 2). The teaching data set consisted of data from 37 cows and the validation data set consisted of data from 36 different cows. The number of measurements used in teaching was 5,074 and 4,868 for validation. Both data sets included measurements from 9 lameness cases and they both included data from primiparous and multiparous cows. From the cows in the validation data set, 7 were diagnosed as lame at some point during the study and, 1 of the cows was diagnosed lame during 2 separate time periods.

Table 2. *Numbers of cows and observations used for model teaching and validation*

					Measurements, no.		
Dataset	Cows	Sound cows	Lame cows	Lameness cases	Total	Sound cows	Lame cows
Teaching	37	36[1]	9[1]	9	5,074	4,790	284
Validation	36	36[1]	8[1]	9	4,868	4,709	159
Total	73	72	17	18	9,942	9,499	443

[1]Eight cows were both sound and lame during different periods of the study.

4.4.3 Model Development and Validation

Selection of the parameters used as model inputs was done by testing the performance of the model with all of the described parameters in chapter data processing and also with different combinations of parameters. Eventually, LWR and the number of kicks per milking were selected as the model inputs because they were found to differentiate most accurately the lame cows from the sound cows. The Neural Network Toolbox of MATLAB (Mathworks, Natick, MA) was used to develop and validate the model. The PNN was taught with the teaching data set using several spread values. The spread value is included as a parameter in the MATLAB function.

The model was first taught with a teaching data set that consisted of measurements (LWR and kicks per milking) along with the correct classification. Then it was validated with a data set independent from teaching data. The model gave a classification of sound or lame for each of the measurements from every cow in the validation data based on the information found in the teaching data set. This is illustrated in Figure 7. Because we only used 2 classes (i.e. sound and lame) for the measurements, the model had only 2 possible outputs: sound or lame.

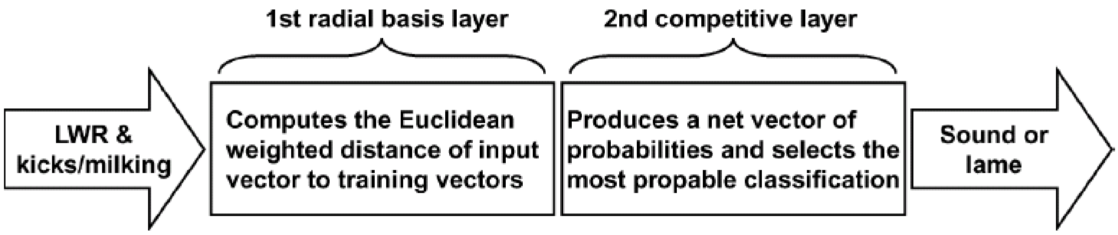

Figure 7 *The operation of the PNN model.*

Performance of the PNN in the classification task was judged by how accurately the model classified the measurements in the validation data (Table 2). The following criteria were used:

1) Detection rate = percentage of lameness cases detected
2) Percentage of measurements causing false alarms (i.e. percentage of measurements coming from sound cows classified as lame)
3) Relative earliness of detection = detection date with the model – the earliest classification date
4) Percentage of the measurements classified correctly
5) Sensitivity (lameness cases detected / total number of lameness cases) and specificity of the model in detecting lame cows (number sound cows classified as lame / total number of sound cows)

5. Results

5.1 Lameness Assessment

During the veterinary inspections, a total of 18 lameness cases were found in 17 cows. Of those cases, 16 resulted from hoof problems and 2 from injuries. Observed hoof diseases were 7 white-line diseases, 8 sole ulcers, and one tyloma with interdigital phlegmon. All of the sole ulcers were located in the sole bulb junction of the lateral claw. The white line separations were mostly situated in the abaxial wall-bulb junction of the lateral claw and some of these in the abaxial white zone of the lateral claw. Mean duration of lameness was 13.7 days with standard deviation of 9 days. This does not necessarily represent the actual duration of the problem, but the time when the cow was milked by the robot with the four balance system. In some cases, cows were moved away from the robot and some problems also overlapped with the break in the research period. All of the observed cases were cured during the study. Data was collected also during the the sound period from 16 of the 17 cows that were found lame at some point. The duration of the sound period ranged from 10 days to 5 months. The incidence of lameness during the research period was 25% and the prevalence varied from 3% to 15%.

5.2 Measurements

An example of the automatically registered leg load during milking is given in Figure 8. The figure shows that the cow was very calm during milking apart from movement in the beginning and the end of milking. The movement can be seen as sharp peaks in the data, which were registered either as kicks or steps as described in data analysis. The decrease in the total weight is due to milking.

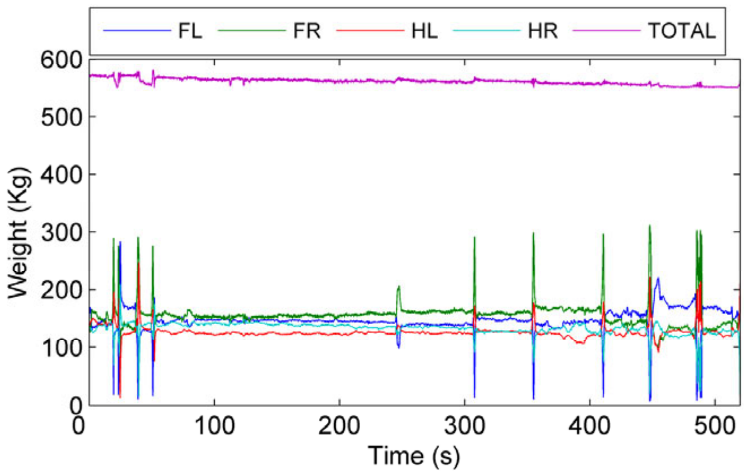

Figure 8 *The leg weights and the total weight of a sound cow during milking.*

The normalized distributions of the parameters LWR (%), standard deviation of the weight (%) of lighter-hind-leg/body–weight during milking and kicks per milking per milking for all of the measurements from sound (n=9,499) and lame (n=443) cows are shown in Figure 9. There is a statistically highly significant (P<0.01) difference between the lame and sound cows according to the Mann-Whitney U-test in all of the above mentioned parameters. Despite the clear statistical difference in the medians, the figure shows that the distributions for all parameters of sound and lame cows clearly overlap, and no single value alone allows us to make the judgement if a cow is sound or lame. This is also why the PNN model is needed to classify the cows into lame and sound groups.

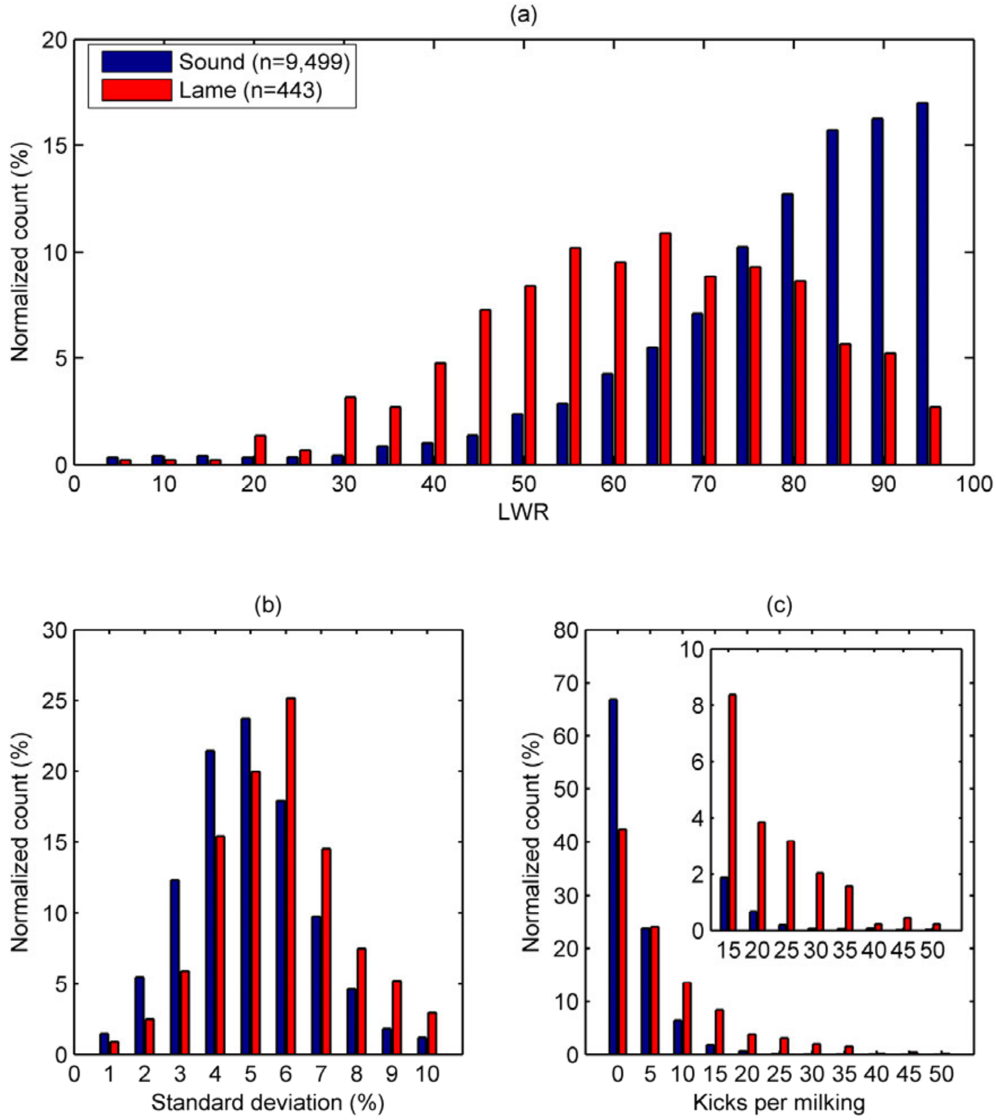

Figure 9 *The normalized distributions of the (a) LWR's ,(b) Standard deviations (%) of the weight of lighter hind leg/body weight and (c) the kicks per milking for sound and lame cows.*

The change in the weight distribution and kicking frequency of the hind legs of one cow with interdigital phlegmon can be seen in Figure 10 and 11. Figure 10 shows the mean hind leg weights and the number of kicks during the development of the problem, and Figure 11 shows the raw data from the hind legs at different stages of the problem. In Figure 11a the cow is still sound, while Figure 11b, 11c and 11d show the leg weight with different degrees of lameness. The disease progressed to severe lameness in just a few days. The figures show that in the mild stage (on 10/21, Figure 10) the cow had started to place less weight on the affected leg (Figure 11b). When the disease progressed to a more painful stage, the cow constantly lifted the affected leg in order to relieve the pain, which can be seen as frequent peaks in the data (Figure 11c) and low mean weight on the affected leg along with an unusually high number of kicks (10/23, Figure 10). In the most severe stage the cow had LS score of 4 and had to be taken away from the robotic milking and placed into quarantine in a separate pen. This can be seen as a gap in Figure 10. The cow barely placed any weight on the affected leg, lifting the leg constantly (Figure 11d). The time difference between the 3 weighings is only 2 days. After the disease was treated, the leg weights returned to normal (Figure 11e). The disease has affected the total body weight of the cow. Figure 11f shows the total body weight of the cow before, during and after lameness. The total body weight clearly decreased during lameness, but returned back to prior level after the disease was cured. The decrease was probably caused by decreased food and water intake because of reduced locomotion during the lameness.

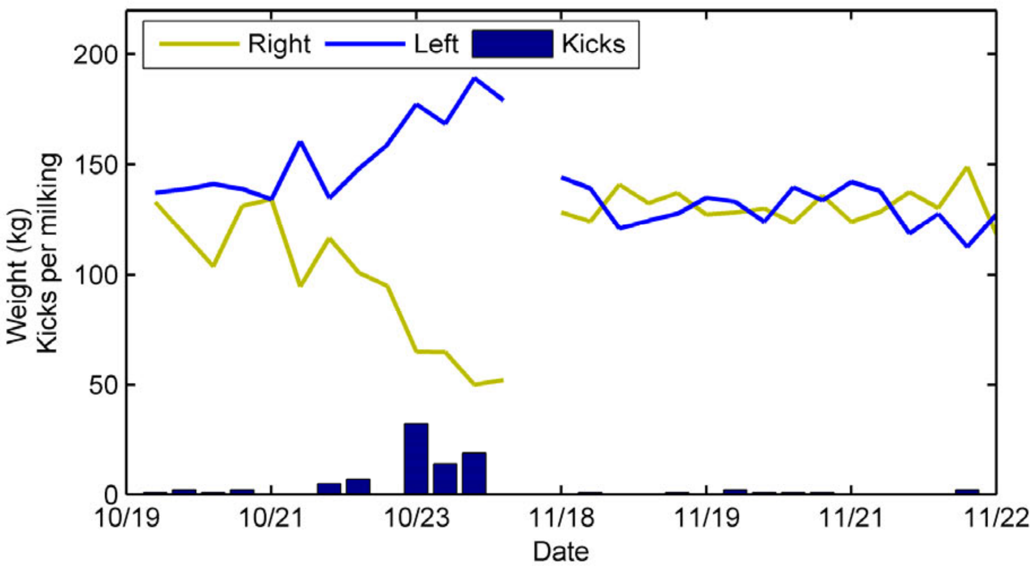

Figure 10 *The development of the mean weight of the hind leg of a cow with interdigital phlegmon. The disease developed to a more serious stage between 10/21 and 10/23 and the cow was quarantined until 11/18 when the disease had healed and the cow is sound again.*

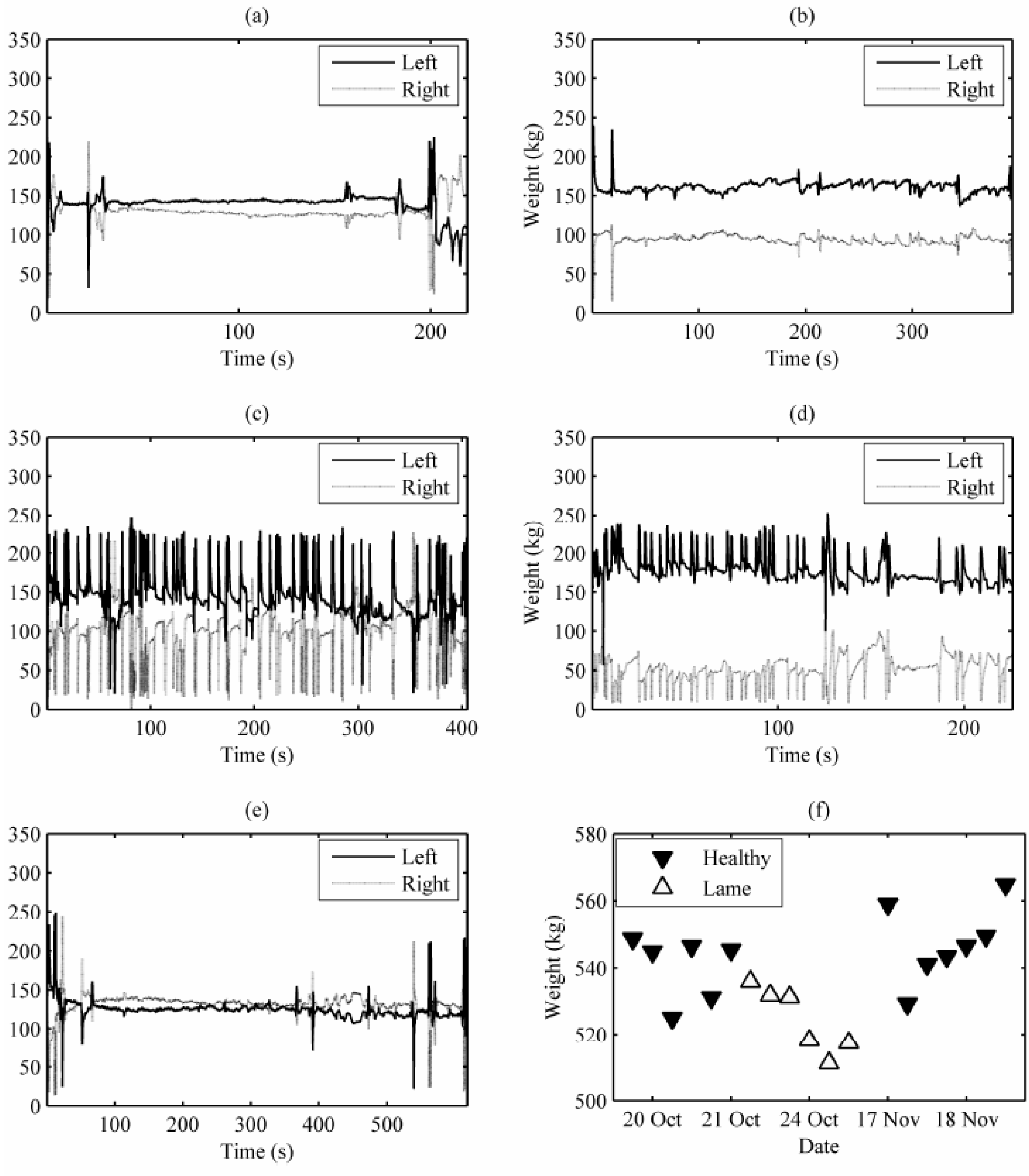

Figure 11 *The weight on the hind legs of a cow during different health states: (a) before lameness (b) early stage of lameness (c) moderate lameness (d)severe lameness (e) after lameness. (f) The change in the total body weight of the same cow before, during and after lameness.*

5.3 The PNN Model in Lameness Detection

The spread values used in the training of PNN had a clear effect on the performance of the network. The effect of spread on the classifying ability of the model is shown in Figure 12. It was decided that the model should achieve the highest possible detection rate, i.e. all of the lameness cases should be identified with the smallest possible amount of false alarms given. Figure 12 shows that the best performance is achieved with a spread of 0.8. With that spread value the overall classifying ability of the model was 96%, with the lameness detection rate 100% and the number of measurements causing false alarms 1.1%. Some of the measurements (=milkings) of lame cows were classified as sound, but this did not decrease the detection rate since all of the cows that were lame gave an alarm during the lame period. With spread values of over 0.8 the detection rate decreased.

Also the relative earliness of alarms with different spread values was looked into. The time of the identification of the problem with the PNN was compared to the time when the cows in the validation set were first classified as lame. The time difference between the first classified lameness date and the detection with the model is called relative detection delay. The average relative detection delays for 9 cows with different spread values and detection rates are shown in Figure 12. It can be seen that increased spread, which means more reliable detection, leads in delayed identification of lameness.

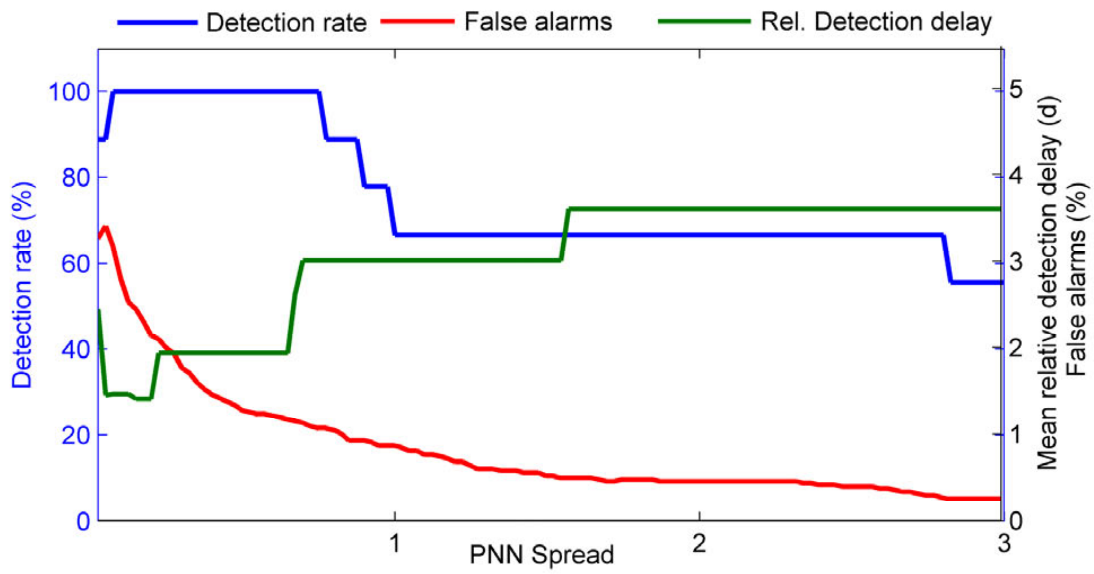

Figure 12 *The effect of PNN spread in the lameness detection rate, relative detection delay and the amount of measurements causing false alarms.*

The effectiveness of the model in detecting lameness cases was evaluated with the help of a ROC curve. ROC analysis is used to evaluate the accuracy of a model's ability to separate positive from negative cases. The discrimination accuracy of a test is described by AUC. An AUC of 1 represents perfect discrimination and area of 0.5 represents no discrimination (Hanley & McNeil 1982, Lasko et al. 2005). Figure 13 shows the ROC curve for the test with different spread (σ) levels. The curve was created by calculating the sensitivity (lameness cases detected / total lameness cases) and specificity (number of sound cows causing false alarms / total number of sound cows) of the model classifications during the entire research period for individual animals in the validation data. This differs from Figure 12, where the classification accuracy is evaluated for each measurement. The ROC curve and the corresponding AUC were approximated using a nonparametric method because it imposes no structural assumptions on the data (Lasko et al. 2005). The curve shows that with a sensitivity of 100%, 42.5% of the cows still caused at least one false alarm over the five month period (AUC = 0.86). This means that even though only 1.1% of measurements give false alarms those, measurements are taken from many different cows.

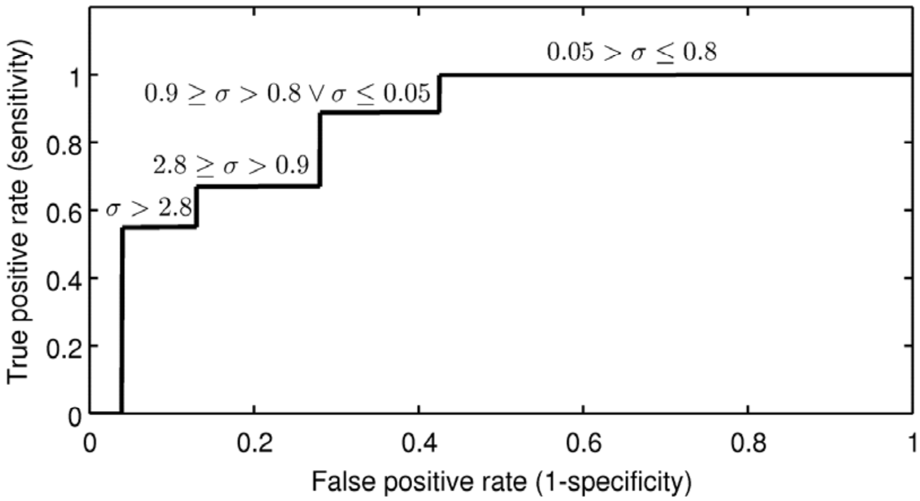

Figure 13 *The ROC curve showing the performance of the model as a diagnostic test for detecting lameness with different spread (σ) levels marked on top of the curve (AUC = 0 .86).*

6. Discussion

6.1 The Measurement System and Data Processing

The leg weights of dairy cows during milking were successfully recorded and algorithms for analysis of raw data were developed. The four balance system collects the leg weight data automatically, which enables multiple daily observations for each cow.

Not all of the measurements were successful because of cows standing outside of the balance platforms, but erroneous values were automatically corrected with algorithms developed in the study (II). The balances were used constantly over several months and were subject to severe loads. The mountings of the sensors had to be repaired and reinforced several times during the study. This was due to the leg loading, because the sensors were not designed for concentrated point loads but for larger load area.

The system evidently operates in milking robots and it could also be used in other regularly visited self-service units such as concentrate feeders. The operation in other units has to be studied separately because the cow behaviour in different situations is expected to differ to some extent.

6.2 The Probabilistic Neural Network Model

A PNN model for lameness detection was developed from the data acquired with the system. A data set of 73 cows was split into two parts for teaching and validation of the model. With the optimal spread value of 0.8, a detection rate of 100% with only 1.1% false alarms was achieved. The model can identify lame cows based on their behaviour and it has data from different degrees of lameness. The fact that the behaviour shown in the cows in this study is similar to that reported in cows by others, e.g. less weight on the affected leg (Neveux et al. 2006, Rushen et al. 2006) and increased kicking frequency (Rousing et al. 2004), indicates that the model may also be used in other farms and herds. This, of course, has yet to be confirmed.

The performance of the model as a diagnostic test for lameness was evaluated with the help of a ROC curve. The AUC was 0.86, which means the test is considered good in separating lame cows from sound cows. The ROC curve was approximated using the nonparametric method as it imposes no structural assumptions on the data (Lasko et al. 2005). With sensitivity of 100%, specificity of 57.5% was achieved. The sensitivity and the specificity describe the amount of cows classified correctly as sound or lame during the entire 5 month research period. This means that if a cow gave a single false alarm during the period it decreased the specificity of the test. However, if the system is used as an on-farm lameness assessment test an occasional false alarm is not that harmful as long as the system can find all of the actual problems. This is because the alarm is not meant to be an incentive to start treatment, but for the farmer to go and check the animal in question and then decide on the action to be taken.

The information about the model behaviour with different spread values can be used when the on-farm use of the system is considered. The system could judge each weighing with several spread values and give alarms with different priority levels for the farmer. Alarms given with small spread values indicate possible leg problems, whereas alarms with high spread values indicate almost certain lameness cases.

6.3 The Usability of the System in Lameness Detection

The system and the developed model can be transferred to on-farm applications, and it works in farms with milking robots. However the performance of the model on different sets of cows and other farms has yet to be confirmed. It is also possible to adapt the model with data from more lameness cases.

Acquiring measurements from more infectious hoof diseases and incorporating those into the model could be beneficial. Early detection of infectious diseases is important so that they are treated before spreading to other cows in the herd. Data from only one interdigital phlegmon was measured during the study and it was easily seen from the data and painful for the cow. This is typical for cows affected by the disease (Manske 2002). Future work should also involve clinical inspection of all non-lame cows to identify all hoof lesions and their effect on the leg weights.

The on-farm use of the system could significantly improve the identification of lameness cases since results from Whay et al. (2003) suggest that farmers are only aware of 25% of lameness cases in their herds. More accurate identification of the problem makes it also possible to treat the problem more efficiently thus leading to both improved animal welfare and improved economic result for the farmers. Nordlund et al. (2004) have suggested that identifying the prevalence and cause of lameness in a herd is necessary for systematic prevention of the problem. The use of automation in detection of health problems also frees up the time for the farmers for other tasks and increases the possibility for leisure time.

Only a few methods for automated lameness detection have been presented so far. Rajkondawar et al. (2002a; 2002b; 2006) were able to successfully separate sound cows from lame cows with their walkthrough system. They also developed gait and lesion based statistical models (Rajkondawar et al. 2006) to detect lame cows and evaluated the performance of the models with ROC curves. They were able to get AUC of 0.84 in the best case. Flower et al. (2005) were able to identify cows with sole ulcers by analysing stride variables from video recordings. However, they had to use reflective markers on the legs of the animals and manually digitize the recordings, so the system was not ready to be used in automated lameness detection.

Van der Tol et al. (2004; 2005) and Carvalho et al. (2005) measured the pressure on different parts of the hoof with pressure sensitive sensors to observe the effects of hoof trimming on the weight balance under the hoof. None of those reports, however, indicated use of their systems in lameness detection.

The four balance system may be more suitable for farms with milking robots than a walkthrough system (Rajkondawar et al. 2002a; 2002b; 2006) or image analysis (Flower et al. 2005) since the barns designed for automatic milking do not necessarily have suitable areas for gait measurements. However the use of the four balance system with the current model is limited to milking robots. With a different model it could probably also be used in automatic feeding systems. This is also supported by the findings of Neveux et al. (2006) and Rushen et al. (2006), who have also utilised a system measuring leg weights and found that discomfort under a hoof causes a cow to bear less weight on the affected leg.

Cattle often mask pain instinctively, which leads to delayed detection and treatment of lameness. Assessment of pain is a crucial issue in veterinary and welfare research, but pain is subjective and it is very difficult to measure (Rutherford 2002, O'Callaghan et al. 2003). The model developed in this study does not allow the comparison of the severity of different problems, because the PNN only classifies the cows to groups sound and lame. Therefore a statistical method to assess the amount of change in the leg weights caused by different degrees of lameness would be useful. Development and validation of such a model, however, requires more time series data from multiple animals with very detailed veterinary inspections.

Major advantages of the four balance system are that it is observer independent and the results are repeatable. Several studies have shown that the results of gait scoring, which is the most common method of assessing lameness, are subjective. O'Callaghan et al. (2003) reported that the intra-observer repeatability in gait scoring for a 5-point numerical scoring system was only 56%, and the interobserver repeatability was only 37%. However, when a one point difference was allowed, the scores for intra-observer and inter-observer repeatability were in agreement for 93% and 81% of scores respectively. Winkler and Willen (2001) found 68% repeatability of scores among 3 observers.

The development and healing of hoof diseases and injuries as well as the effect of hoof treatment and medication can be seen in the leg weight data as the condition of the animal changes, which has also been found by Rushen et al. (2006). This makes it possible to use the system when evaluating the effect of treatments or when studying the development of different diseases.

7. Conclusions

A fully automatic lameness detection system that operates in a milking robot was developed in the study. The instrumentation, measurement software, algorithms for data analysis and a neural network model for lameness detection were developed. The following conclusions are drawn about the system:

1. The leg weights and the step and kick behaviour of cows can be automatically and reliably measured with the system.
2. Erroneous values can be automatically removed from the data with the developed algorithms.
3. The changes in leg weights can be used to analyse the development of lameness and the effect of treatment.
4. The system is a good diagnostics test in separating lame cows from sound cows with the developed neural network model.

Further studies should include more measurements from different cows with very detailed veterinary follow up of the development of lameness, with focus also on pain. This would enable the development of a statistical method to objectively assess the duration of lameness and the amount of change in the leg weights caused by different degrees of lameness. The model could provide an objective measure to assess severity of lameness from the leg weight data and thus make the system even more useful in veterinary research.

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