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CAN SENSOR TECHNOLOGY BENEFIT MASTITIS CONTROL

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SUMMARY

Since the 1980s, efforts have been made to develop sensors that measure a parameter from an individual cow. One of the first techniques was a sensor that measures the electrical conductivity of milk. Application of electrical conductivity in practice only took a start with the introduction of the automated milking system. The aim of this review is to provide a structured overview of the published sensor systems for udder health management.

The development of sensor systems can be described by the following four levels: I. techniques that measure something about the cow (e.g., milk electrical conductivity, EC); II. interpretations that summarize changes in the sensor data (e.g., increase in milk EC) to produce information about the cow's status (e.g., mastitis); III. integration of information where sensor information is supplemented with other information (e.g., economic information) to produce an advice (e.g., whether to treat a cow or not); and IV. the farmer makes a decision or the sensor system takes the decision autonomously (e.g., milk is discarded).

This review has structured a total of 31 publications from 2002-20012 describing 37 sensor systems for mastitis detection and compared them based on the four levels. Many studies presented sensor systems at levels I and II, but none did so at levels III and IV. Most of the work for mastitis (92 per cent) is done at level II.

The performance of sensor systems varies based on the choice of gold standards, algorithms used, and test sizes (number of farms and cows). Studies on sensor systems for mastitis have shown that sensor systems are brought to a higher level, however there is still a need to improve detection performance. No systems with integrated decision support models have been found.

INTRODUCTION

An important development in Western Europe is the use of automated milking systems (AMS). The first studies on the feasibility of an AMS were done in the mid-1980s, such as the initial preliminary study by Rossing et al. [1]. The first commercial farms introduced an AMS in the Netherlands in 1992 and by 2009 the number of farms using an AMS had increased to more than 8,000 worldwide (90 per cent of which were located in Western Europe) [2]. In the operational management of farms, the use of an AMS will require a different strategy for the detection of mastitis. When using an AMS, there is no milker present who could visually judge the cows' foremilk for the presence of clots to detect mastitis. Therefore, farmers must rely on alternative methods to detect mastitis. Since the 1980s, work has been done on devices that measure a health indicator in, up, on, or from an individual cow [3]. Examples of sensors include milk electrical conductivity and milk colour sensors [4]. However, these sensors were never commercially successful. Therefore, the introduction and success of the AMS was an important boost for the development of sensors for automated mastitis detection.

In general, there is a trend in dairy farming towards the automation of processes in order to reduce (physical) labour and labour costs [2,5]. This development is partly driven by the economic reality of increasing labour costs relative to capital costs. Automated systems enable dairy farmers to manage larger herds with lower labour requirements [2], which means that the application of both the AMS and sensor systems fits within the trend of increasing herd sizes.

The objective of this review is to provide a structured literature review of the sensors, sensor data, data algorithms that provide information, and the corresponding decision support systems to be used in mastitis management. This paper describes four key points: (1) Level I: 'Sensor technique': what sensor systems are developed for the detection mastitis; (2) Level II: 'Data interpretation'; (3) Level III 'Integration of information"; and (4) Level IV 'Decision making. Finally the system quality will be discussed in terms of sensitivity and specificity of the detection, how informative the system is for the farmer and what aspect of the system are important for considering its performance and information.

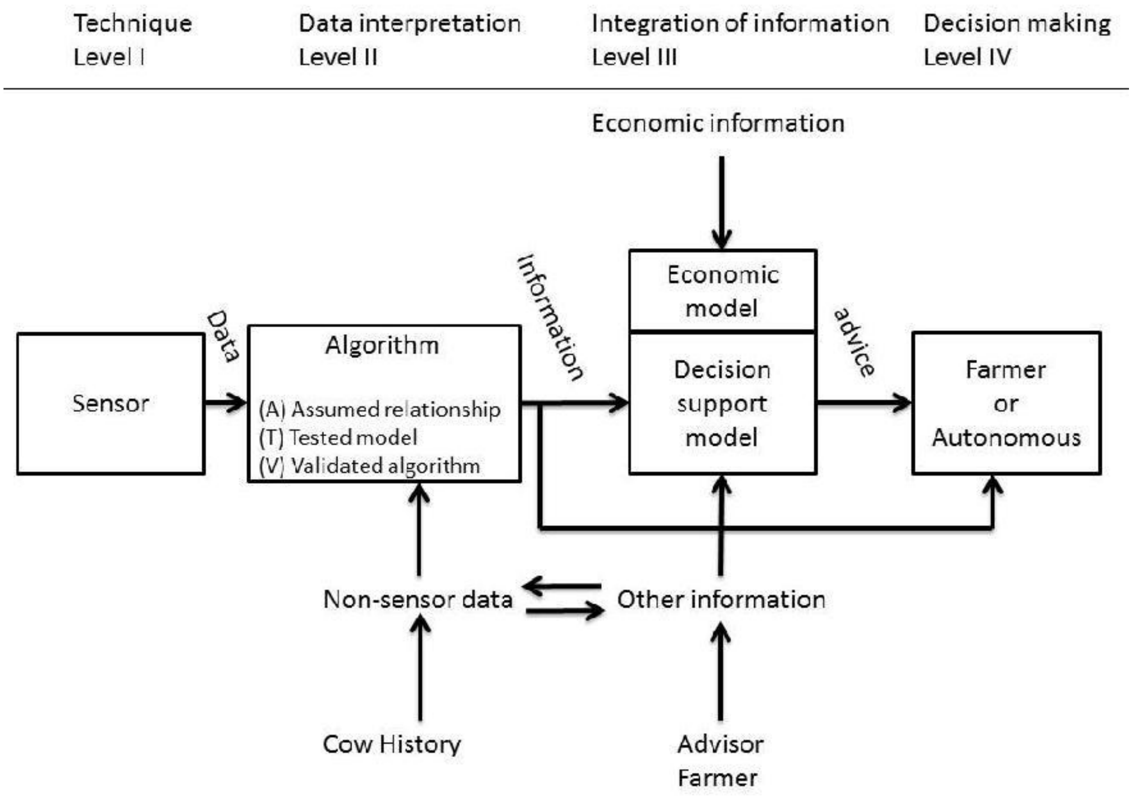
MATERIALS & METHODS

This study considers a sensor to be a device that measures a physiological or behavioural parameter (related to udder health) of an individual cow and enables automated, on-farm detection of changes in this condition that is related to a health event (such as mastitis) and requires action on the part of the farmer (such as treatment).

There are two categories of sensors: attached and non-attached. Attached sensors may be on-cow sensors that are fitted on the outside of the cow's body, or in-cow sensors that are inside the body (for example, rumen bolus or implant). Non-attached sensors are off-cow sensors that cows pass by, over, or through for measurement. Two specific forms of non-attached sensors are in-line and on-line sensors. In-line sensors take measurements in a continuous flow of a product from the cow. The only available option for in-line measurement is in the milk line. On-line sensors automatically take a sample (milk, for example) that is analysed by the sensor.

Framework

Figure 1 Framework of the development stages for sensor systems that can be used to support dairy farm health management.



This review has used the scheme shown in Figure 1 to categorize sensor systems. The scheme shows a framework that describes the steps from a sensor to a decision. Sensors are categorized in the levels of this scheme according to their description in the literature. Sensors are only described if they reach at least level I, known as “technique,” which means that they measure an aspect of the cows’ condition or status. The two categories identified within this level are solely measuring a parameter and an assumed relation. In some sensors the produced data is processed by a data algorithm (for example an AMS measures electrical conductivity of milk that flows through the milk line, the data algorithm calculates the average conductivity over the whole milking).

The next step (level II) is called “data interpretation” and measures changes in the sensor data to produce information about the cows’ status (e.g., mastitis). The two categories identified within this level are an a statistically tested relation and a validated algorithm. From a statistically tested relation, it is possible to build a predictive model (detection algorithm) that classifies the cows’ status (for example, mastitis or healthy). For validation, a data set (not the one used to build the detection algorithm) is used to assess the performance by comparing the classification of the algorithm with the gold standard. A further feature can be updating or resetting the detection algorithm with gold standard measurements during operation in practice, this would mean the algorithm adapts to an individual farm or changing circumstances.

Level III integrates the sensor information with other information (such as economic information), to produce advice for the farmer. Furthermore, information of individual cows can be aggregated by a monitoring algorithm at the herd level. The output of this algorithm can be seen as either general information on the herds health for the farmer or additional data input for the detection algorithm. The decision is eventually made either by the farmer or autonomously by the sensor system (level IV, known as "Decision making").

Having gained a clear overview of the available sensor systems, the data and information produced by these sensor systems was compared. The quality of the data and information (that is, whether the data or information was fit for use by farmers) was assessed. The criteria for this assessment were whether the sensor system detects a clearly defined change in the cows' health (such as clinical mastitis or high SCC) and presents this change clearly to the farmer (such as in the form of an alert rather than as a graph of sensor data). Also, detection sensitivity and specificity were discussed in respect to the used gold standard and the test scale. Furthermore, the added value of the sensor system for the farmer's decision making was discussed. This comparison led to a discussion of what further research would be needed to improve performance of available sensor systems, develop new sensors and make sensor systems that can be used in practice for udder health management on farms and are of more practical value on-farm.

Literature selection

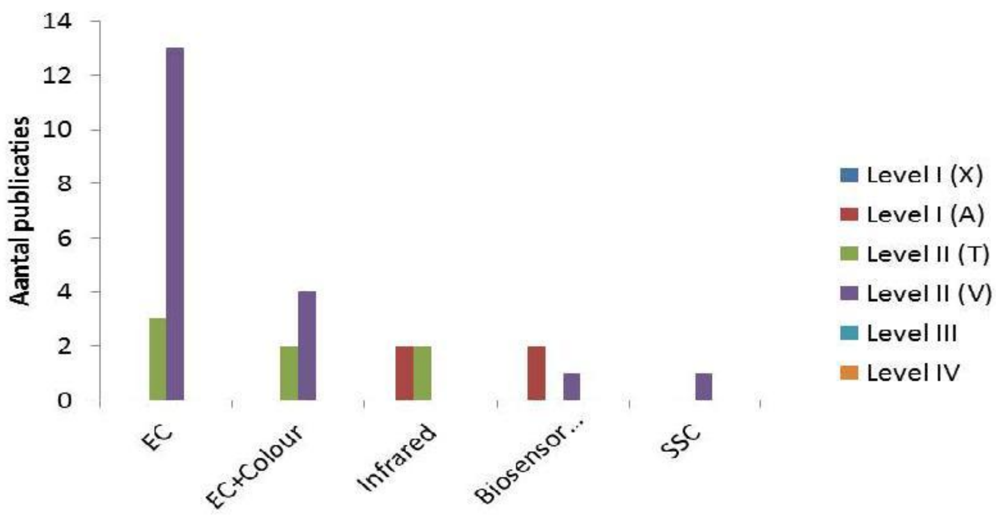
The relevant literature was searched based on keywords including sensors, dairy farming, and automated detection, in combination with words such as mastitis, and udder health. Literature was also identified by a forward search, using the citations and a backward search using the references of the papers found through the keyword search. Journals from the ISI database (Web of Science, Thomson Reuters, New York, USA) were used for the period from January 2002 until June 2012, and the proceedings of relevant scientific conferences held between 2007 and 2012 were searched. The conferences included the First North American Conference on Precision Dairy Farming (Toronto, 2010) and the European Conference on Precision Livestock Farming (Prague, 2011 and Wageningen, 2009).

RESULTS

Level I: 'Sensor technique'.

For automated detection of mastitis, 31 publications were found with 37 described sensor systems (some publications described multiple sensors, algorithms, or diseases). Four (11 per cent) of these publications were proceedings papers. Electrical Conductivity (EC) was the main sensor system studied (in 15 studies, 48 per cent), followed by a combination of EC sensors and milk colour sensors (seven studies, 23 per cent). Some other studies used a biosensor to detect certain enzymes, including haptoglobine, L-lactate dehydrogenase or NAGase (five studies, 16 per cent), an SCC sensor (two studies, 6 per cent), or a reticular bolus that measured temperature (one study, 3 per cent). The EC and milk colour sensors were in-line sensors, meaning that they measure in a continuous milk flow. The biosensors and SCC sensors took measurements from automatically collected milk samples, meaning that they were on-line sensors. The bolus was inserted in the cow's reticulum, which made it an in-cow sensor.

Figure 2 Sensor for automated detection of mastitis per level of development according to Figure 1.



Level II: 'Data interpretation'.

Figure 2 shows that 34 (92 per cent) published sensor systems for automated detection of mastitis included data interpretation, which means that the (statistical) relation between gold standard (e.g., the California Mastitis Test (CMT)) and sensor measurements (e.g., milk EC) was studied. For 27 (73 per cent) studies the algorithm was validated (that is, they used a data set to calculate predicted mastitis classification per cow and compare these with the gold standard). For 15 (41 per cent) sensor systems, the sensitivity and specificity of the detection algorithm were determined and reported; this is discussed further below.

Level III 'Integration of information'.

Figure 2 shows that none of the sensor systems integrated the sensor information with other information.

Level IV 'Decision making'.

Sixteen (43 per cent) sensor systems provided the farmer with a mastitis alert, while 12 (32 per cent) also provided a probability added to this mastitis alert to describe the certainty, and two (5 per cent) provided a degree or classification of mastitis. Eight (22 per cent) sensor systems provided the farmer with raw sensor data (such as milk NAGase concentration) and/or were unclear in describing what they provided to the farmer.

DISCUSSION

Literature has shown that mastitis is currently one of the main health issues on dairy farms [14,15,16]. Therefore detection of mastitis cases is important, especially in the light of increasing herd sizes and increasing application of the AMS.

For mastitis (92 per cent of the publications on mastitis sensors) most work is done on level II of Figure 1. Most studies on mastitis (73 per cent of the publications on mastitis sensors) described a validated algorithm. For mastitis 8 per cent of the studies describe a sensor with nothing more than an assumed relation between mastitis and sensor data. Test scales of the studies vary considerably. Studies on sensors for mastitis all included more than 10 cows, indicating that very small test scale were not found in current literature. The effect of test size on detection performance is unclear, as publications with different test sizes also vary in one or more other aspects (such as sensor type, algorithm, or gold standard).

A variety of mathematical models have been used to build algorithms for automated detection and these algorithms also vary greatly in reported sensitivity and specificity. No sensor systems have been found to match the ISO standard for sensitivity and specificity, which has been formulated as appropriate for automated detection of mastitis. Due to the large variation in performance, the algorithms used, and the study design, it is not possible to make general statements on the appropriateness of the algorithms.

The output (together with detection performance) of a sensor system determines the value for the farmer. Raw sensor data requires farmers to interpret the data themselves in order to determine whether something has changed in the cow's health status. When the sensor system contains an algorithm that produces an alert, the interpretation for the farmer is been made easier as it gives a clear statement about the cow's health status (the reliability of this statement is a different issue). Within the alerts, mastitis alerts are informative for the farmer as these alerts do regard a specific condition.

System quality

Detection performance, which is described by sensitivity and specificity, varies considerably. The reported sensitivities ranged from 55 per cent to 89 per cent, while reported specificities ranged from 56 per cent to 99 per cent. For the sensor systems studied, a trade-off exists between sensitivity and specificity as high sensitivity (> 80%) is combined with low specificity and vice versa. None of the studies reported a combination of high sensitivity and high specificity. Moreover, none of the studies met the ISO/FDIS 20966 limit of 80 per cent sensitivity with 99 per cent specificity. Although one sensor system reported a sensitivity of 100 per cent and a specificity of 99 per cent for a combination of SCC and EC measurements, these values were based on nine positive gold standard cases. Some variation in test scale was reported: 10 publications reported that their sensor system was tested on more than one farm, where the others tested their sensor system on only one farm.

EC is the most studied sensor technique for mastitis detection and in some cases it was combined with milk colour sensors. Algorithms have been built for most of these sensors, many of which have been validated. Although the biosensors and SCC sensor have been tested, it is unclear whether these sensors show a better performance than EC sensors. Infrared cameras have been tested, but only assumed relations with mastitis are available. Therefore, it is unclear how these could perform as a mastitis sensor. Even if systems do not meet the ISO limit, the value that an automated mastitis detection system provides to a farmer is obvious, as the alternative is having no automated detection at all. Especially for those farmers using an AMS or managing a large herd the need for a sensor system is present. However, the perfect mastitis alert does not seem to have been found.

Due to the large variation in reported performance, gold standards, test scales, and algorithms used, it is difficult to compare the performance of various sensor types. For example, sensitivity in the range of 83 to 92 per cent with specificity between 75 and 94 per cent were reported for a fuzzy logic algorithm with SCC as a gold standard [6]. Other studies using a fuzzy logic algorithm [7,8], do not report a comparable performance. When visual judgment of milk is used as a gold standard, naive Bayesian networks (70 per cent sensitivity and 97.8 per cent specificity) [9] and artificial neural networks (91 per cent sensitivity and 87 per cent specificity) [10] show the best detection performance. The detection performances under two different gold standards for different algorithms are hardly comparable. Of the used gold standards, visual judgment of milk and CMT had the advantage that they could be performed easily and on-farm, while SCC requires lab analysis. It is difficult to say which of these gold standards is the most appropriate; on one hand, SCC might be more accurate, while on the other hand, visual judgment and CMT might be done more frequently. For EC, in combination with milk colour sensors, good performance has been reported (84.6 per cent sensitivity and 99.4 per cent specificity) [11], with treated CM cases as a gold standard. Because it is not clearly known how many of the occurred cases of CM have been treated, this gold standard's reliability is questionable at best. As a result it is only sure that treated cases were CM cases, how many untreated cases of CM are detected or remain undetected by the sensor system remains unknown. Therefore, the reported performance of such a sensor system should be treated with caution. The Herd Navigator® (DeLaval, Tumba, Sweden), which automatically takes and analyses milk samples, seems to perform good (80–82 per cent sensitivity and 98 per cent specificity) [12,13], although this is only based on two non-peer-reviewed studies published in conference proceedings and the used gold standard is unclear. When EC is compared with EC in combination with milk colour sensors, sensitivity and specificity seem to be lower for the combination of the two sensor types. Accordingly the EC sensors are tested on a smaller scale (number of cows and/or number of farms) than the combination of EC and milk colour sensors. An explanation for this observation could be that variation between farms (and between cows) influences the detection performance of the sensor systems. However, it cannot be concluded whether this difference should be attributed to the sensor system or to the difference in test scale. The text should go in here.

Gold standard

The choice for a gold standard is important for the detection performance of a sensor system. How well a gold standard reflects reality determines the number of 'true' cases used for algorithm development and validation. If true cases of disease are missing, or false cases are included in the gold standard data (visual observation and scoring system are sensitive for this problem), then the processes of algorithm building and validation will be affected. As cases will be missing or false cases will be included in the data set the algorithm will be misspecified and in the validation some alerts will be wrongly classified as false positive or false negative. In a more practical sense, the intended purpose of a sensor system is important when choosing a gold standard. For the substitution of labour by capital – which means that the sensor system will do a farmer's job – a gold standard that reflects a farmer's detection capabilities could be appropriate. However, for an early warning system, the gold standard should be able to correctly pick up disease or oestrus at an early stage. Another example of the relation between gold standard and intended purpose is detection of clinical mastitis for which visual judgement of milk for clots is appropriate. By contrast, using SCC and CMT as gold standard would include detection of subclinical cases. It is also important to consider the frequency at which the gold standard is determined in the studies. Overly long intervals between gold standard assessments will result in missed true cases, whereas short intervals increase the workload involved, and consequently the cost of the experiments. An example of an overly long interval could be using monthly SCC estimates from milk quality controls as a gold standard. This would result in missed (sub)clinical mastitis cases or late detection of (sub)clinical mastitis cases in the reference data used to build and validate a detection algorithm.

Time resolution

Time resolution (also referred to in the literature as the time window of detection) can be split up into two slightly different concepts. The first is the time resolution of the sensor, including measurements, interpretation, and detection. The second is the time resolution of validation, which means matching of alerts to gold standard measurements in a defined time period.
The frequency used to record measurements of the sensor have an influence on the minimal time of detection. Furthermore, an increased number of measurements decreases the influence that erroneous measurements have on predictions of the detection algorithm. For the detection algorithm, the frequency with which it produces information about a cows' health, based on sensor data, partly determines the time between changes in the cows' physiology and the farmer being informed of the change. Obviously, the time between detection and informing the farmer also depends on the farmer. Technical innovations (like smartphones) might be able to help inform the farmer with sensor information more quickly. The time between the change in the cow's health in reality and informing the farmer is also important in relation to various diseases. For instance, a locomotion problem, although painful, does not require the farmer's immediate attention, whereas oestrus only has a limited period during which successful insemination is possible.
As both the gold standard and sensor system information are point estimates that are measured or determined with their respective frequencies, validation studies must match these point estimates to each other. For mastitis, an in-depth analysis has been conducted of the influence that "time resolution of validation" has on sensor system performance and its use in practice [3]. A longer time period for matching gold standard and alerts generally results in higher sensitivity and specificity. Early detection can be accomplished by producing information regarding the cows health before clinical signs of disease occur (Hogeveen et al., 2010). However, information provided by the detection algorithm after the onset of disease postpones treatment, whereas the farmer may perceive information prior to onset as a false alert, they consider a maximum 24 hours before onset of the disease as desirable [17]. For oestrus detection there cannot be much debate about the fact that a timeframe of about 24 hours is needed to enable insemination after an oestrus alert. For locomotion and metabolic problems the time component is less clear, as the detected conditions (diseases) of the cow remain unclear. Therefore it in unknown what a farmer should do with the information, let alone the farmers preferences can be studied.

In the literature used for this review, it was not always clear whether the term "time window of detection" referred to the "time resolution of the sensor" or the "time resolution of validation." In addition, for the "time resolution of the sensor," often only one or two single aspects, such as the frequency the sensor used to take measurements, were mentioned. What is more, the literature only discussed aspects of the time resolution briefly, if at all. So, considering the publications in the review, the time resolution of the sensor systems remains a greatly neglected aspect in publications.

Studies on decision support and economic considerations of management decisions are available for mastitis, but they are not integrated in a sensor system. For mastitis, decision support systems provide advice for clinical cases [16,18,19,20]. However, subclinical mastitis may be detected by a sensor system and could be relevant as a sub-clinical case could develop into clinical mastitis or chronic subclinical mastitis. Literature is currently available that describes the treatment effectiveness and economic implications of treating subclinical mastitis [21,22,23,24]. Treatment of persistent sub-clinical mastitis is economically profitable for many cows when indirect effects of cure are considered (that is, prevention of clinical flare-ups and transmission to other cows) [23]. However, most studies on sensor systems for mastitis still focus on detecting clinical mastitis and do not determine sub-clinical cases for which treatment would be profitable. Another limitation is that many decision support systems were developed to support cow health management when milking in a milking parlour. However, the current trend in Western Europe is the use of AMSs, which have changed the operational management on dairy farms dramatically. A few studies have focused on pathogen specific treatment of mastitis, although the economic merit of pathogen specific treatment seems to be absent [20].

CONCLUSIONS

Most of the work for mastitis (92 per cent) is done at level II. Most published studies for mastitis clearly describe what disease they are aiming to detect, and most of these studies focus on the performance of the sensor system

For sensors systems, there is no clear difference in the performance of various algorithms. Detection performance of the sensor systems varies based on the choice of gold standards, algorithms and test sizes (number of farms and cows). The most important remark for further sensor research is to have a clear aim of what information about the cows health should be produced by the sensor system under study. In respect to the aimed information an appropriate gold standard, algorithm, test size and time resolution should be chosen.

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