MINING SENSOR DATA TO DISCOVER CLINICAL MASTITIS

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Abstract

When cows are milked with an automatic milking system (AMS), clinical mastitis (CM) cannot be detected adequately without using electronic sensing devices. This paper describes approaches to improve automated CM detection in AMS using sensor inputs and data mining. Sensor data and observational CM data, both at quarter level, were collected over two years at nine Dutch AMS farms. Decision-tree induction was used for model development using data from cows that were highly likely to be healthy or that were clearly suffering from CM. The model was validated including quarter milkings with a less clear CM status. A decision-tree was developed with sensitivity of 40% and specificity of 99% using a strict time-window (<24h) to coincide CM alerts and observations. Increasing the time-window to a suggested practical level (three days) increased sensitivity to 69.5% at the same specificity. In comparison to currently applied models, the decision-tree showed an improvement in CM detection, but the proposed sensitivity and specificity requirements were not achieved. Improvements in detection performance are expected when new sensor information (e.g. on-line somatic cell count sensors) is added.

Introduction

Worldwide, dairy farmers produce milk that has to meet certain milk quality standards. Although legislation dealing with these quality standards may differ between countries (e.g., Regulation (EC) No. 853/2004; United States Grade A Pasteurized Milk Ordinance; NZCP1: Code of practice, Version 5), they all require that abnormal milk, and milk from diseased (e.g. due to a clinical mastitis (CM) infection) or injured udders should be excluded from milk supplied for human consumption. They also agree that milkers are responsible for detecting abnormal milk, or methods achieving similar detection results are used. When milking in a parlor, detection can be done by a visual check of milk stripped from each quarter before cups are attached. However, when milking with an automatic milking system (AMS) there is no milker present during the milking process. To safeguard milk quality, it is essential that AMS use sensors. Detection models for CM process data collected by sensors during milking with AMS to generate a mastitis alert list. This reports cows likely to have CM that need a visual check by the farmer. The search for a perfect CM detection model – putting all cows with CM infection on the mastitis alert list without listing any cows erroneously – has been long. Automated CM detection models predominantly use electrical conductivity measures at cow or quarter level (Hogeveen et al., 2010). Despite research efforts to develop CM detection models that meet suggested detection requirements (sensitivity (SN) >70%; specificity (SP) >99%; Mein and Rasmussen, 2008), those currently used by AMS have an SN of 36.8% and an SP of 97.9% (Mollenhorst and Hogeveen, 2008). There is a clear need to improve automated CM detection models under field conditions. It would also be beneficial for detection models to provide information about the causal pathogen. Three options merit exploration to improve automatic detection of CM using sensor data from AMS: 1) applying alternative algorithms for data pre-processing and classification, 2) adding information from other sensors, and 3) adding additional cow-level information, e.g. parity and somatic cell count (SCC) history. This paper summarizes several studies of these approaches to improve automated CM detection using sensor data from AMS.

<u>Applying Alternative Algorithms for Data Pre-processing and Classification or Prediction</u>

Data pre-processing: Mean or maximum values of electrical conductivity have been used as predictive variables for CM. Absolute values, differences between values from all quarters, and differences between values from previous milkings are most often used. However, mean and maximum values are not the only descriptors or variables that can describe a sensor measurement pattern. Better information might be obtained with other or additional sensor measurement descriptors. Therefore, a new concept of data pre-processing was implemented to develop new predictive variables based on sensor measurements of electrical conductivity, milk yield and color, measured within quarter milkings, for potential use by automated CM detection models (Kamphuis et al., 2008a). Data were collected on one AMS research farm in Germany. Figure 1 describes steps used to transform raw data from sensor measurements at quarter level into predictive variables that express level, variability, shape of sensor output data. These were evaluated for their ability to detect CM by computing correlation coefficients and gain ratios. Results showed CM detection models may benefit from combining sensor data describing several milk characteristics or using variables that describe other sensor measurement pattern aspects than the mean and maximum value. Sensor measurements of electrical conductivity and milk color in the blue and green spectra showed the most potential for CM detection. Variables based on absolute sensor measurement values may be as important as variables based on expected values from previous quarter milkings or expected values based on other quarters.

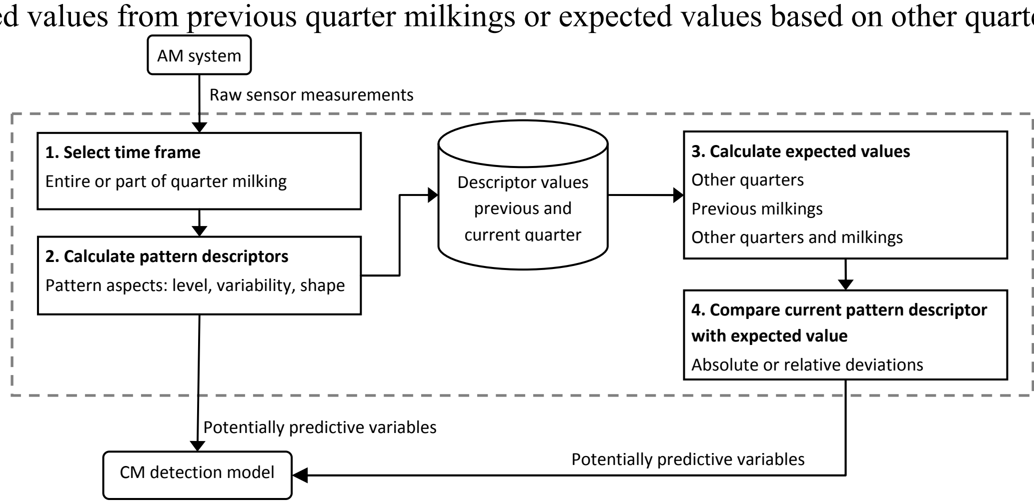

Figure 1. Data flow diagram representing steps to transform raw sensor data from individual quarter milkings into potentially predictive variables (from: Kamphuis et al., 2008a).

Data classification and prediction: Decision-tree induction, an analysis method often used for classification (Quinlan, 1986), is believed to deal with unbalanced, noisy and incomplete data. These three characteristics apply to problems associated with data from automated CM detection systems: the low prevalence of CM results in data for analysis to be highly skewed, and sensor data are by definition noisy and potentially incomplete due to malfunction or inadequate calibration. The application of decision-tree induction methodology for automated CM detection used data collected during a two-year study on nine Dutch dairy farms with AMS (Kamphuis et al., 2010). Sensor data of electrical conductivity, milk yield, and color were available for 3.5 million quarter milkings, of which 348 had CM according to observations by participating farmers. Data were divided into training (two-thirds of all data) and test sets. Decision-trees were trained, with and without bagging and boosting (data mining techniques used to retrieve more informed decisions), with data from 243 quarter-milkings with CM and 24,717 quarter milkings with a very high likelihood of being healthy. They were validated using data from 105 quarter milkings with CM and a random sample of 50,000 quarter milkings without a CM observation.

The decision-tree developed in combination with bagging techniques showed the best detection performance (Table 1). This decision-tree had 40% SN and 99% SP when a strict time-window of <24h was used so that CM alerts coincided with observations. This detection rate was similar to that of models currently used by AM systems (SN = 36.8%; Mollenhorst and Hogeveen, 2008), but the number of false positive alerts was reduced by more than 50%. The large variation in gold standard definitions, data used, and time-windows applied made direct comparison with previously reported results difficult. Sherlock et al. (2008) suggested that the most practical time-window would be from 48h before a CM observation until 24h after. When this extended time-window was applied, SN increased to 69.5% with a SP of 99%, close to the suggested requirements of Mein and Rasmussen (2008). Furthermore, the developed CM detection model should be suitable for practical application because model building and validation were based on actual field data from commercial farms, alerts for CM had to be given within a narrow time-window of less than 24h before CM were observed, and detection performance was based on a test set that included quarter milkings with uncertain mastitis status, closely mimicking practice (Hogeveen et al., 2010). In an additional study to explore the use of sensor data for CM pathogen prediction, decision-tree induction was applied to 140 CM cases (110 Gram-positive cases) with both sensor data and bacteriological culture results (Kamphuis et al., 2011). Data were divided into training (n = 96) and test sets (n = 44). The decision-tree developed had an accuracy of 90.6% based on data in the training set. When only CM cases with high probability estimates for their Gram-status (either positive or negative) were considered, 74% of records in the training set could be classified with a stratified accuracy of 97.1%; however accuracy dropped to 54.5% when the model was validated. It was concluded that decision-tree induction was not able to use the sensor data for Gram-status prediction.

Adding New Sensor Information

Kamphuis et al. (2008b) explored the value of including data from in-line measurements of somatic cell counts (SCC) for individual cow milkings for detection of CM (Data were collected from a research farm applying AMS in a pasture-based dairy system (Greenfield Project, Hamilton, New Zealand). Clinical mastitis was defined as quarters that were treated for mastitis with antibiotics. Three models were compared; the first model used electrical conductivity as the sole criterion for udder health, the second used SCC data only, and the third applied a fuzzy logic model to combine the two. With SN fixed at 80% for all, the false alert rate per 1,000 cow milkings and the detection success rate were similar between the first two models. When both information sources were combined, the false alert rate was reduced 2- to 3-fold, and detection success rate increased by 2- to 3-fold. The fuzzy logic model had SP of 99.8% at the fixed SN level of 80% (Table 1). It was concluded that the CM detection model performed better when on-line somatic cell count information at cow-milking level was added to electrical conductivity measurements.

Adding Non-sensor Information

The opportunity to improve CM detection performance by adding non-sensor information was explored by Kamphuis (2010). Cow information was added to a modified version of the CM detection model developed by decision-tree induction in combination with bagging as described above. The modification involved transforming a CM probability at quarter level to a CM probability at cow level. The CM detection model based on sensor data alone provided a prior probability estimate for a cow milking to be a CM event. Posterior probability estimates were calculated after probabilities of CM based on non-sensor cow-level information (e.g. parity and SCC history) were added. Adding cow-level information did not improve detection performance (Table 1). Contrarily, the model with combined information had a lower detection performance than the model based on sensor measurements alone.

Table 1. Detection performance (Sensitivity (SN) and Specificity (SP)) of clinical mastitis detection models using sensor data from AMS

Applied algorithm	**Sensor information used**	**Cases[1] (n)**	**Non-cases[1] (n)**	**Time-window (h)**	**SN (%)**	**SP (%)**
DTI[2]	EC[3], color, yield	243	24,717	<24h	24.7	99
DTI & boosting	EC, color, yield	243	24,717	<24h	38.1	99
DTI & bagging	EC, color, yield	243	24,717	<24h	40.0	99
DTI & bagging	EC, color, yield	243	24,717	48h[4]	66.7	99
DTI & bagging	EC, color, yield	243	24,717	72h[5]	69.5	99
Fuzzy logic	EC, SCC[6]	18[7,8]	27,699[7]	72h[5]	80[9]	99.8[9,10]
DTI & bagging	EC, color, yield	261[7]	259,785[7]	<24h	26.3	99
DTI & bagging & NBN[11]	EC, color, yield, cow information	261[7]	259,785[7]	<24h	20.2	99

[1]Number of records used for training a model at quarter level. [2]Decision-tree induction. [3]Electrical conductivity. [4]Divided into 24h before a CM observation and 24h after a CM observation. [5]Divided into 48h before a CM observation and 24h after a CM observation. [6]Somatic Cell Count measured at cow level. [7]Based on cow milkings. [8]CM cases were defined as quarters treated with antibiotics for mastitis. [9]Performance based on training set, no additional test set was used for validation. [10]Approximately, using ‘false alert rate ≈ 10 * (100 – specificity)’ (Sherlock et al., 2008). [11]Naïve Bayesian network.

Decision-tree induction can deal with sensor data collected in the field even though these data are noisy, incomplete, and unbalanced. When a strict time-window (<24h) was applied, SN was 40% and SP was 99%, indicating that decision-tree induction can improve detection performance compared to currently used models. Widening the time-window to three days increased SN to 69.5% with SP of 99% using sensors that measure electrical conductivity, color, and yield. While these models show performance improvements, current sensor technology does not achieve proposed detection requirements and it is unlikely that further algorithm development will result in further progress, thus other approaches are needed to improve automated detection. Inclusion of in-line SCC measurements at cow level improved CM detection performance, and SCC measurements at the quarter level can be expected to provide further improvement (Mollenhorst et al., 2010). Song et al. (2010) reported on a new generation of color sensors which show promising results for CM detection. The results presented here indicate that new sensor information is the most likely route to improve CM detection in the future. New developments such as sensors working in the near infrared spectrum and measuring lactose dehydrogenase (Hogeveen et al. 2010) need to be evaluated for their potential to improve CM detection.

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