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Bayesian integration of sensor information and a multivariate dynamic linear model for prediction of dairy cow mastitis

Dan B. Jensen,*[1] Henk Hogeveen,† and Albert De Vries‡
*Department of Large Animal Sciences, University of Copenhagen, DK-1870 Frederiksberg C, Denmark
†Chair Group Business Economics, Wageningen University, 6706 KN Wageningen, the Netherlands
‡Department of Animal Sciences, University of Florida, Gainesville 32611

ABSTRACT

Rapid detection of dairy cow mastitis is important so corrective action can be taken as soon as possible. Automatically collected sensor data used to monitor the performance and the health state of the cow could be useful for rapid detection of mastitis while reducing the labor needs for monitoring. The state of the art in combining sensor data to predict clinical mastitis still does not perform well enough to be applied in practice. Our objective was to combine a multivariate dynamic linear model (DLM) with a naïve Bayesian classifier (NBC) in a novel method using sensor and nonsensor data to detect clinical cases of mastitis. We also evaluated reductions in the number of sensors for detecting mastitis. With the DLM, we co-modeled 7 sources of sensor data (milk yield, fat, protein, lactose, conductivity, blood, body weight) collected at each milking for individual cows to produce one-step-ahead forecasts for each sensor. The observations were subsequently categorized according to the errors of the forecasted values and the estimated forecast variance. The categorized sensor data were combined with other data pertaining to the cow (week in milk, parity, mastitis history, somatic cell count category, and season) using Bayes' theorem, which produced a combined probability of the cow having clinical mastitis. If this probability was above a set threshold, the cow was classified as mastitis positive. To illustrate the performance of our method, we used sensor data from 1,003,207 milkings from the University of Florida Dairy Unit collected from 2008 to 2014. Of these, 2,907 milkings were associated with recorded cases of clinical mastitis. Using the DLM/NBC method, we reached an area under the receiver operating characteristic curve of 0.89, with a specificity of 0.81 when the sensitivity was set at 0.80. Specificities with omissions of sensor data ranged from 0.58 to 0.81. These results are comparable to other studies, but differences in data quality, definitions of clinical mastitis, and time windows make comparisons across studies difficult. We found the DLM/NBC method to be a flexible method for combining multiple sensor and nonsensor data sources to predict clinical mastitis and accommodate missing observations. Further research is needed before practical implementation is possible. In particular, the performance of our method needs to be improved in the first 2 wk of lactation. The DLM method produces forecasts that are based on continuously estimated multivariate normal distributions, which makes forecasts and forecast errors easy to interpret, and new sensors can easily be added.
Key words: mastitis, Bayesian classifier, dynamic linear model

INTRODUCTION

Mastitis is associated with a wide range of characteristics that can be measured in milk. In a classic review, Kitchen (1981) described the effect of mastitis on the composition of milk and discussed potential diagnostics based upon these effects. In addition to SCC, electrical conductivity, milk constituents (especially lactose), and enzymes (such as *N*-acetyl-β-D-glucosaminidase and lactate dehydrogenase) have been identified to be affected by clinical mastitis.

Since the 1990s, work has been carried out on automated detection of mastitis using changes in one or more milk characteristics (e.g., Nielen et al., 1992). Automated mastitis detection systems started to be widely used on commercial dairy farms with the introduction of automatic milking systems approximately 20 yr ago. A mastitis detection system consists of at least 2 elements: the sensor (hardware) and the algorithms to translate sensor data into alerts (software). A decision support system and a decision-making system may also be part of a mastitis detection system (Rutten et al., 2013). The main sensor (hardware) used to detect mastitis measures electrical conductivity (e.g., Nielen et al., 1995b; Norberg et al., 2004; Cavero et al., 2006).

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[1]Corresponding author: daj@sund.ku.dk

Sensor systems based on other milk characteristics, such as milk color (Song et al., 2010), lactate dehydrogenase (Chagunda et al., 2006; Friggens et al., 2007), and SCC (Whyte et al., 2005; Mollenhorst et al., 2010), have also been proposed and are available on the market.

Most publications on automated mastitis detection systems are aimed at the algorithm for transforming sensor data into alerts. Significantly different data-modeling techniques have been proposed, including thresholds (e.g., Mollenhorst et al., 2010), moving averages (Maatje et al., 1992), neural networks (e.g., Nielen et al., 1995b; Cavero et al., 2008), fuzzy logic (e.g., de Mol and Woldt, 2001; Kamphuis et al., 2008), time series analysis (de Mol et al., 1999; Cavero et al., 2007), discriminant function analysis (Norberg et al., 2004; Kamphuis et al., 2010), and wavelet filtering (Miekley et al., 2013). In most of these studies, electrical conductivity was combined with other measurements (mostly with milk yield) to improve the performance of the detection system.

So far, the performances of the published mastitis detection systems do not satisfy the high accuracy needed for practical clinical mastitis detection systems (Hogeveen et al., 2010). Combining data from more sources has been suggested as a possible method for improving the performance of mastitis detection systems. It remains unclear how to best combine data from different sensors and from other sources, including accounting for missing observations. Bayesian analysis has been used as an approach to prioritize sensor data–based alarms by including cow-specific information (Steeneveld et al., 2010).

Most mastitis detection systems compare observed sensor values to forecasted values and monitor forecast errors. Forecasts are typically based on moving averages (e.g., Maatje et al., 1992), but if the quality of the forecast is improved, then the performance of a mastitis detection system may be improved as well.

As a method for combining the many possible lines of sensor- and non–sensor-based data for a unified prediction of mastitis, we propose using a multivariate dynamic linear model (**DLM**) in combination with a naïve Bayesian classifier (**NBC**). The multivariate DLM provides the forecast values, whereas the NBC combines all available observations, including forecast errors, with a prior probability to achieve a single posterior probability of mastitis.

A property of the multivariate DLM, as described by West and Harrison (1997), is that it is adaptive, and thus the expected values are automatically adjusted to the longer term trend of the data. Another property of the multivariate form of the DLM is that the codependencies between several variables of interest can be taken into account when one-step-ahead forecasts for these variables are calculated, which is attractive for the NBC.

Similar adaptive forecasting has been applied by Huybrechts et al. (2014), who used a synergistic control process to adjust lactation curves in an effort to use milk yield as a predictor of clinical mastitis (sensitivity: 0.63). Huybrechts et al. (2014) relied heavily on a specific mathematical model for long-term forecasting, whereas the adaptive and short-term nature of the forecasts produced by a DLM allows for a freer description of multiple (non)linear trends that may predict the short-term observations better. Furthermore, the DLM easily handles missing data because one-step-ahead forecasts are always produced given the available data.

Few applications of DLM for monitoring animal production systems exist. Univariate implementations of the DLM have been developed for applications including detection of estrus in sows (Ostersen et al., 2010) and describing the drinking behavior of young pigs (Madsen and Kristensen, 2005). To our knowledge, no previous descriptions of applications of a multivariate DLM exist for detecting diseases in production animals, such as mastitis in dairy cows.

An NBC classifies a new set of observations by estimating the probability that the observation belongs to each class (mastitis or healthy). The NBC is a relatively simple classification method, but it has been shown to be useful in a wide range of fields, such as prediction of bacterial thermophilicity (Jensen et al., 2012), diagnosis of classical swine fewer (Geenen et al., 2011), and detection of clinical mastitis (Steeneveld et al., 2009). The NBC has advantages over comparable classification methods, such as artificial neural networks or logistic regression functions, because missing observations can be easily handled in an NBC by including only the observations that are available. Similarly, adding data from a new sensor is relatively trivial with the NBC, so long as likelihoods are available for the outputs of that sensor, associated with the outcome variable that needs to be classified. Such likelihoods may be estimated from scientific literature or practical knowledge of how mastitis influences milk characteristics and cow physiology, or they may be derived directly from observations made on site using the sensor. Lastly, the likelihoods make it easy to see the relative contributions of the various variables of interest, as opposed to the black-box nature of, for example, neural networks.

A combination of a DLM and NBC is therefore a potentially attractive practical method to detect clinical mastitis using data from multiple sources. This study had 2 objectives: (1) to describe and illustrate the combination of a multivariate DLM and a NBC for detecting clinical mastitis, and (2) to measure the performance of the DLM/NBC method and estimate the