Recognition of Activity States in Dairy Cows with SVMs and Graphical Models

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Abstract: Activity patterns of dairy cattle have received increasing interest in recent years because they promise insights into health state and well-being. The fusion with data from additional sensor signals promises a comprehensive monitoring of activity patterns composed of sequences of single activity states. We used a combination of a Support Vector Machine (SVM), a state of the art classification method, and a Conditional Random Field (CRF). SVMs distinguish single states, whereas CRFs label state sequences under consideration of specified constraints. In a preliminary experiment, a Local Positioning System was combined with a heart rate sensor in order to estimate seven spatiotemporal activity states. The application of the CRF to the SVM result caused a slight increase in accuracy (5%) but a major improvement at the correct determination of long sequences (increasing length of the longest common subsequence from 3481 to 6207 periods). This robust detection of long lying sequences allowed for the unaffected extraction of the resting pulse.

1 Introduction

Optimal conditions and continuous monitoring are a major factor for achieving optimum levels of animal welfare with high performance dairy cows. Activity patterns are sensitive indicators for animal welfare - consequently many sensors have been applied for the automatic monitoring of cow activity patterns. The limiting factor for the monitoring of dairy cattle is the versatility of activity states, each with individual characteristics. These versatile distinguishing features may be covered by a high number of specialized sensors or more efficiently by a combined analysis of complementary sensors. For this data fusion we utilized the Machine Learning methods SVM and CRF. Our objective was to develop a model that is able to derive the most probable activity state for every observed point in time (the spatiotemporal activity pattern) for every individual cow. In a preliminary experiment, a combination of two sensor types was used in order to deduce reliable information about seven activity states. Two sensor systems were used: a local position measurement system and a heart rate sensor.

2 Methods for Data Analysis

The data analysis methods were applied in three steps within the derivation process of the activity patterns. In the first step, spatiotemporal features were extracted from filtered sensor data. The position and heart rate were synchronized and thereafter joint spatio-temporal features were extracted. The position features are based on spatial knowledge about the layout of the cattle barn and included the distances to important objects like cubicles and feeding stations. The heart rate sensor recorded the heart rate (HR) together with a time stamp at intervals of one second. In addition to the HR, the most common heart rate variability (HRV) parameter (RMSSD; in ms) and additional features which are gained by the Recurrence Quantitative Analysis [MLN02] was added to the feature set.

In the second step, preliminary probabilities for activity states were derived by a multiclass Support Vector Machine (SVM) [CV95]. SVMs are state of the art methods for supervised classification and provide linear and non-linear discrimination functions [CV95]. The SVM model consists of a subset of weighted data instances - so called support vectors. They define a hyperplane separating classes in the feature space. The distance of a feature vector to the hyperplane is transformed to class probabilities. The used SVM achieved a prediction accuracy of 79.01% for the classification of activity states. Consequently it outperformed the widespread Naive Bayes approach (56.33%) and is comparable to the Random Forest classifier (78.03%).

In the last step, these probabilities were linked with each other and combined with contextual knowledge by a Conditional Random Field (CRF) [LNP01]. The probabilities of the unobserved variables were computed given the evidence of observed variables in the inference step. When applied for activity state recognition, the observation nodes were realized by the class probabilities derived by the SVM model. The edges between the label nodes describe a semi-Markov process. This facilitates the duration dependent control of the model inertia. Two different functions for the transition probabilities for the different activity states were used: a linear model for fast state transitions ("feeding", "drinking" and "walking") and sigmoidal model for a longer persistence in a state ("lying" and "standing"). Specific transitions in the resulting sequence e.g. direct transition from "lying" to "drinking" are prohibited by these functions. Thereby, it was forced that the states "standing up" and "walking" has to occur intermediately. Hence, the generated time series of labels are always valid from the viewpoint of physical constraints of the cattle in the barn. The positive effects of the graphical model as refinement of the SVM result are based on the inclusion of three additional priors: (i) consecutive points in time have most probable the same state, (ii) some state transitions are impossible and (iii) the duration of different states follows different distributions.

3 Exemplary Application

An exemplary application was implemented at a herd of 65 German Holstein Friesian cows which were loose-housed in a two-row open free-stall barn with cubicles and concrete floor. The study regarded seven activity states "standing", "lying", "walking", "feeding", "drinking", "standing up", and "lying down" defined in a protocol and used as labels for the training data (manual annotation). The observations were taken at three periods for at least 4 hours in the morning (from 07:00 am to 12:30 pm). 12 cows were selected to cover the herd range of lactation numbers, social status and day of pregnancy and overall, 43 complete and plausible time series were recorded.

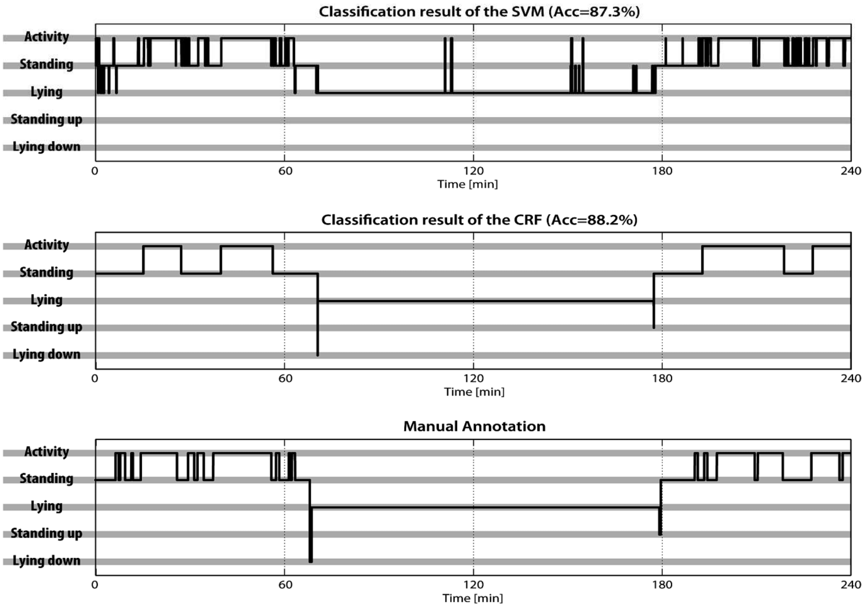

Figure 1: Prediction of activity states showing the different characteristics of the SVM classification result and the result of the graphical model. From left to right: (a) classification result of the SVM with prediction accuracy, (b) classification result of the CRF with prediction accuracy and (c) the manual annotation. The state “activity” comprises the states “walking”, “feeding” and “drinking”.

As position sensor the Local Position Measurement system (LPM, Abatec group AG, Austria) based on runtime measurement was applied [GNB07]. In the cow barn, shadings and reflections and the small distances between the installed antennas greatly impair sensor signals. The accuracy of x- and y-coordinate fluctuates between 10 cm and 4 m. The z-coordinate was neglected for an improved accuracy in the remaining dimensions [GNB07]. For the measurement of HR and the HRV, sensors from Polar Electro GmbH (Büttelborn, Germany) were used (Polar Equine RS800, Polar Equine RS800CX). The electrodes were integrated in a chest belt (Polar Equine WearLink® W.I.N.D. transmitter) and the signals were transmitted wireless to a data logger.

4 Results and Discussion

The presented method of analysis combining feature extraction, SVM classification, and graphical model derived the most probable sequence of activity states. One exemplary time series is presented in Figure 1 showing the accuracy of the classification by the SVM and its improvement by the additional use of the graphical model. Long sequences like "lying" were classified without single errors, which enabled the robust extraction of parameters like "longest lying sequence" or "number of standing up events". This focus is considered by utilizing the additional quality measurements “Longest Common Subsequence” (LCS) and average “Common Subsequences” (CS) which demonstrates the improved result quality of the CRF (Table 1). The point in time of "standing up" and "lying down" was correctly determined.

Evaluation step	Count of state	Mean lengths of	Mean length of	Accuracy “Lying”	Accuracy “Standing”
SVM	327.72	3481	107	84%	81%
CRF	6.12	6207	1271	86%	89%

Table 1: Comparison of classification results of the SVM and the CRF. Prediction quality is assessed by prediction accuracy in percent, the Longest Common Subsequence (LCS), and the Mean Length of all “Common Subsequences” (CS).

The automatic detection of resting sequences by the analysis method in combination with the recorded signal of the heart rate sensor allowed for the automatic determination of the stable pulse rate while lying. The mean resting pulse rate (RPR) of individual animals varied from 64.9 to 81.0 bpm (SD = 4.86 bpm). The mean SD of the RPR of an individual cow was 1.96 bpm (within the range of 0.29 to 3.66 bpm). Furthermore it was noticed that the automatically derived RPR depended significantly on the respective stage of pregnancy ($p = 0.049$; by Kruskal-Wallis H Test). Increasing resting heart rate with duration of pregnancy of women is well documented.

The developed transition model supports the robust determination of "standing up" and "lying down" sequences (Figure 1), although this information is not accessible by a single sensor. HR and HRV help to identify these processes which are not covered by the LPM and enable the automated recognition of spatiotemporal activity pattern. The presented, integrated analysis uncovers this information because it combines the outstanding generalization ability of the SVM and the duration dependent sequence model of the CRF. The analysis method can be applied to data of additional sensors like rumination sensors or pedometers, whereby the prediction quality will continue to improve and further states like "rumination" will become accessible.

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