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Behavior classification of cows fitted with motion collars: Decomposing multi-class classification into a set of binary problems

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ABSTRACT

Precision management systems for livestock offer the potential to monitor and manage animals on an individual basis. A key component of these sensor based systems are the analytical models that automatically translate sensor data into different behavioral categories. A new methodology was proposed for multi-class behavior modeling based upon the “one-vs-all” framework. This methodology differs from the standard approach to behavior classification where a single classifier is trained to discriminate between multiple behaviors. Instead a set of binary classifiers are trained to each discriminate one of the behavior classes against a combined class of all the remaining behaviors. The confidence scores from the set of binary classifiers are then combined to generate a behavioral estimate.

The performance of this new modeling approach is validated across a study involving 24 Holstein-Friesian dairy cows that were each fitted with an Inertial Measurement Unit (IMU) on a collar upon their neck. Five general classes of cow behavior grazing, walking, ruminating, resting and “Other” were classified. Binary time series classifiers were tailored to each of the five behaviors through training and validation of each model across a range of configurations including nine window sizes, five classifiers and a feature selection process of 84 candidate input features.

Results revealed that the proposed model classified grazing behavior with an extremely high classification accuracy (*F*-score of 0.98), whilst ruminating and resting behaviors were also classified with a high accuracy (*F*-scores of 0.87 and 0.85, respectively), and walking was classified with a lower accuracy (*F*-score of 0.73). The proposed model offered a 5% performance improvement over standard multi-class time series classifiers that was attributed to the “one-vs-all” framework training a classifier for each behavior independently; this created diversity in the behavior model.

The feature selection process used in developing each of the binary classifiers found that features representing the motion intensity and pitch of the cow's head were most important to each of behavior's classification. Whilst a minor performance improvement was obtained using the proposed methodology, it is suggested that further performance improvements could be obtained by increasing the diversity of the classifier's inputs. Diversity could be created by fusing the data of other sensors that can be fitted to the cows i.e. GPS tracking unit, pressure sensor and microphone.

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1. Introduction

Precision management of livestock differs from traditional herd management by tailoring decisions to the individual animal. The aim of precision strategies is to maximize the genetic potential of each animal and ensure resources are allocated efficiently on the farm. An animal's behavioral interactions with its physical environment must be continuously monitored for precision management strategies to be successfully implemented. The observed behaviors

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of each animal must then be linked to management knowledge in areas such as breeding, welfare and nutrition to enable the appropriate action to be taken. For instance, illness can be predicted in cattle when there is a reduction in the level of social interaction, rumination and feed intake (Weary et al., 2009; HealthyCow24, 2016). Furthermore, other behavioral changes have been shown to be indicative of when cattle are lame (von Keyserling et al., 2011), in estrus (MooMonitor+, 2016; Herd Intelligence, 2016), in pain (Gonzalez et al., 2010) or under heat stress (Allen et al., 2013).

Sensors and digital technologies are becoming an important enabler for precision livestock management. Sensor based monitoring systems offer the potential for continuous and autonomous monitoring of cattle without the need for human involvement. Such systems generally consist of a sensor or suite of sensors that are fitted to each animal and a model that uses the sensor data to infer the animal's behavior. Commercial monitoring systems classify the basic behaviors of a cow, but most importantly, compare the classified behaviors to rules regarding the animal's expected or normal behavior in order to alert of potential management issues (MooMonitor+, 2016; Herd Intelligence, 2016; HealthyCow24, 2016).

Behavior models classify the time series acquired from sensors by differentiating between the behavior classes based upon their unique motion characteristics. Models use sets of contiguous time series segments from either a 3-axis accelerometer to represent the motion and/or orientation of the leg, neck or head of the cattle (Martiskainen et al., 2009; Robert et al., 2009; Smith et al., 2015; Dutta et al., 2015; Gonzalez et al., 2015; Oudshoorn et al., 2013; Ueda et al., 2011), a microphone to capture the sound associated with cattle behavior (Ungar and Rutter, 2006; Schirmann et al., 2009) or a GPS method to represent spatial movement patterns (Anderson et al., 2012; Ungar et al., 2005; Homburger et al., 2014; de Weerd et al., 2015). These models are commonly known as time interval based classifiers.

The simplest behavior models are known as binary models and detect a single behavioral event (Ungar and Rutter, 2006; Delagarde et al., 1999; Schirmann et al., 2009; Ueda et al., 2011; Oudshoorn et al., 2013) or differentiate between a pair of behaviors (Braun et al., 2013; Nielsen et al., 2010). For instance, the grazing behavior of cows was detected by computing relevant thresholds from the accelerometer data (Ueda et al., 2011; Oudshoorn et al., 2013) or microphone data (Ungar and Rutter, 2006), whilst a moving average filter was used to discriminate between the standing and walking behavior of cows (Nielsen et al., 2010). Binary models are simple to develop given they are comprised of few parameters, and hence, easy to optimize. As models are developed to classify a greater number of behaviors, the class decision boundaries become increasingly complex. A high-dimensional parameter-space becomes necessary to discriminate between the classes. Consequently, machine learning methods are commonly adopted for problems with multiple behavior classes (Martiskainen et al., 2009; Robert et al., 2009; Smith et al., 2015; Dutta et al., 2015; Gonzalez et al., 2015; Anderson et al., 2012; Ungar et al., 2005; Homburger et al., 2014; de Weerd et al., 2015) given it provides the necessary tools to estimate complex class decision boundaries in high-dimensional space.

One of the problems with multi-class classifiers is that they have been designed with a “one size fits all” strategy in mind where the objective is to select the model type, set of input features and window duration that minimize the expected classification error across all behaviors jointly. Hence, the optimal representation of all of the behaviors jointly is likely to be suboptimal for some of the individual behaviors. One example is the ruminating behavior of a cow that is characterized by a unique repetitive chewing motion of the rumen bolus. When an accelerometer is attached on the neck of a cow, the features repre-

senting the cow's rhythmic jaw motion can be used to classify rumination. It could be found these same set of features are not useful to discriminate a number of other behaviors (i.e. resting, walking, standing), and hence, reduce the overall performance of a multi-class classifier.

Unlike multi-class classifiers that may compromise the performance of individual behaviors to maximize the performance of the group of behaviors, binary classifiers are trained to optimally discriminate between each pair of behaviors, and hence, avoid this compromise. This paper presents a new approach to cattle behavior classification where the multi-class problem is reduced to a set of simpler binary classification problems. The “one-vs-all” classification framework (Rifkin and Klautau, 2004) is adopted by training a single binary classifier for each behavior with the target behavior being classified against a combined class of all the remaining behaviors. In our adaptation, the model configuration of each classifier is independently selected in order to maximize the classification performance of the respective target behavior. To solve the multi-class problem, the behavior associated with the binary classifier offering the highest classification confidence (class posterior probability) is selected as the mutually exclusive behavior.

In this paper, we compare this new approach to behavior classification to commonly used behavior models for a 3-axis accelerometer that is fitted to the cow's neck. Classifiers are trained for each of the four behaviors comprising 90–95% of a cow's daily activity; grazing, walking, ruminating and resting (Kilgour, 2012). To tailor each binary classifier to its associated behavior, a search is performed to find the optimal configuration with respect to the type of classifier, input feature set and window duration. In contrast to the other “black box” approaches to modeling animal behavior, the optimal configuration of each binary classifier is interpreted with respect to the motion characteristics of the behavior.

2. Materials and methods

The “one-vs-all” framework is presented to train a set of binary models that each represent one behavior class against a combined class of all the remaining behaviors. The outputs of the models are then fused to provide complete coverage of cow behavior in the paddock. The methodology that is presented here can be replicated for any behavior classification study.

2.1. “One-vs-all” classification framework

The problem is formulated for a data set $Z = [X Y]$ composed of input samples X and associated behavior labels $Y \in C$ where $C \in \{c_1 \dots c_K\}$ are the set of K behavior classes. Instead of using Z to train a single multi-class classifier, a set of K binary classifiers (B) are trained. Each binary classifier is trained using the instances of one behavior class against a combined class of the remaining behaviors. To infer the behavior of a new instance, the class estimates of the K binary classifiers are combined.

2.1.1. Tailoring classifiers to each target behavior

The binary classifiers are independently trained to enable each classifier to be individually configured. As part of the training, a search process is adopted to identify the type of classifier, the set of input features and window size used to classify each behavior.

2.1.2. Fusing binary classifiers

Binary classifiers produce a binary label indicating if the target class is detected (“1”) or not detected (“0”). The classification of each input instance could be performed upon the set of K labels created by the binary classifiers. Fusing binary labels is not a valid

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