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A real-time algorithm for acoustic monitoring of ingestive behavior of grazing cattle

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ABSTRACT

Assessment of both grazing behavior and herbage intake are two very difficult tasks that can be concurrently accomplished by means of accurate detection, classification and measurement of grazing events such as chews, bites and chew-bites. It is well known that acoustic monitoring is among the best methods to automatically quantify and classify ingestive and rumination events in grazing animals. However, most existing methods of signal analysis appear to be computationally complex and costly, and are therefore difficult to implement. In this work, we present and test a novel analysis system called Chew-Bite Real-Time Algorithm (CBRTA) that works fully automatically in real-time to detect and classify ingestive events of grazing cattle. The system employs a directional wide-frequency microphone facing inwards on the forehead of animals, and a coupled signal analysis and decision logic algorithm that measures shape, amplitude, duration and energy of sound signals to iteratively detect and classify ingestive events. Performance and validation of the CBRTA was determined using two databases of grazing signals. Signals were recorded on dairy cows offered either, natural pasture ($N = 25$), or experimental micro-swards in indoor controlled environment ($N = 50$). The CBRTA exhibited a simple linear complexity capable to execute 50 times faster than real-time and without undermining overall recognition rate and accuracy when signals were processed at 4 kHz sampling frequency and 8 bits quantization. Furthermore, CBRTA was capable to detect ingestive events with a 97.4% success rate, while achieving up to 84.0% success for their classification as exclusive chews, bites or composite chew-bites. The methodology proposed with CBRTA has promising application in embedded microcomputer systems that necessarily depend on fast real-time execution to minimize computational load, power source and storage memory. Such a system can readily facilitate the transmission of processed data through wireless network or the storage in an onboard device.

1. Introduction

Accurate monitoring of livestock grazing behavior is necessary to ensure that most basic requirements of animal health and welfare are met and consistent with practices that can assure sustainable and efficient use of grazing resources. Hence, different efforts have been put into finding most appropriate techniques to measure and monitor diet and feeding behavior of free-grazing animals (Hodgson et al., 1996; Delagarde et al., 1999). One possible and reliable way is through the detection of distinct jaw movements associated with three common basic events: bites, chews and compound chew-bites (Milone et al., 2012). A grazing bite includes the apprehension and severance of herbage, while a grazing or rumination chew includes the crushing, grinding and processing of consumed herbage. The chew-bite is a third important grazing event that results from the overlapping of chewing and biting on a same jaw movement. Thus, jaw movements can serve as a reliable measure of distinct grazing and rumination cycles. Furthermore, the quantification of rumination chews could provide rich information on the ruminal fermentation of fiber and correlated changes in rumen pH (Sauvant, 2000). Likewise, herbage intake rate appears to depend on trade-offs between ingestive bites, chews and chew-bites, and the monitoring of these events could therefore inform on the ability of grazing herbivores to modulate changes in intake rate (Laca et al., 2000). While the

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number and characteristics of grazing and rumination events vary according to several plant, animal and environmental factors, they could be monitored as indicators of animal health, welfare or nutritional status (De Boever et al., 1990). To the best of our knowledge, only few studies have been focused on developing automated systems to monitoring changes in grazing and rumination.

One plausible approach to measure feeding behavior is acoustic monitoring. Alkon and Cohen (1986) and Alkon et al. (1989) used acoustic biotelemetry to study the feeding behavior of porcupine. Laca et al. (1992) instrumented an inward-facing microphone on the forehead of steers to register stronger and readily distinguishable sounds of bites, chews and chew-bites. Consequently, acoustic monitoring proved to be a more effective methodology to discriminate sensitive differences in feeding and rumination than previous jaw recorders or visual observation methods (Ungar and Rutter, 2006), and since then it has been increasingly applied as a research tool to study different aspects of grazing behavior in sheep and cattle (Galli et al., 2006; Galli et al., 2011).

Broad application of acoustic monitoring continues to depend on suitable algorithms for automatic recognition of sound signals associated with chewing and biting. Milone et al. (2009) used concepts of automatic speech recognition and Hidden Markov Models (HMM) to develop an algorithm for both detection and classification of chewing and biting. The algorithm successfully detected 89%, 58%, and 56% of chews, bites and compound chew-bites in grazing sheep, respectively. Galli et al. (2011) further tested this algorithm to demonstrate the feasibility of using acoustic variables to estimate herbage dry matter intake in grazing sheep. Subsequently, Milone et al. (2012) developed a new algorithm that hereafter will be referred as CBHMM (Chew-Bite Hidden Markov Model) that extended upon previous HMMs. The CBHMM was developed for both detection and classification of chews, bites and chew-bites, in grazing cattle; obtaining up to 85% successful recognition rate.

In an independent development Clapham et al. (2011) adapted the use of SIGNAL software (Engineering Design, Berkeley, CA) for analysis of grazing sounds in cattle. The software was operated on a careful calibration to detect bites in the band of 17–22 kHz, and on a high-pass filter with cutoff frequency at 600 Hz to attenuate background noise. The software detected bites with a 95% confidence, but it seems to demand careful and site-specific calibration before it can be used with different animals, pastures or experimental conditions. The capacity of the recording device and power source were among other limitations of the proposed system.

Navon et al. (2013) implemented an algorithm that used a machine-learning approach to analyze time-domain features (i.e., shape, intensity, duration and sequence of events) of ingestive sounds in grazing cattle. The procedure eliminated the need of calibrations and allowed a detection of ingestive events with a 94% correct and 7% false identification. More recently, Tani et al. (2013) applied pattern recognition techniques to iteratively measure eating and ruminating events collected by a single-axis accelerometer. The recognition patterns were defined in frequency domain and used to identify and classify likely eating and rumination events. Without previous calibration, recognition results were similar to previous analytical procedures used by Clapham et al. (2011) and Navon et al. (2013). However, likely limitations of the methodology were associated with the spectral similarities between rumination and eating signals, presence of non-stationary background noise, and high computational cost associated with the analysis of signals sampled at high frequency.

Although several of the previous instrumentation and analytical procedures have shown good performance for detection of signals associated with eating and/or rumination, few of them offered possibilities to accurately classify exclusive bites, chews and chew-bites, which is a necessary condition for reliable measures of grazing behavior and even for estimation of herbage intake by means of acoustic methods. Furthermore, most if not all of previous methodologies deal with high quality and long duration signals (hours or days) that can demand collection, recording, storage, transfer and analysis of data by means of computationally complex and costly procedures, that can quickly undermine their application as fast, efficient and timely monitoring systems.

The main objectives of the present work were: (1) to develop a novel algorithm called CBRTA (Chew-Bite Real-Time Algorithm) that can be executed in real-time for automatic and efficient identification and classification of chews, bites and chew-bites, (2) to provide an analysis of the computational complexity of CBRTA, (3) to examine the operational performance of CBRTA as a function of modifications in algorithm parameters, and (4) to provide a validation of CBRTA for both detection and classification of ingestive events in cattle by using two databases of acoustic monitoring of dairy cows grazing either outdoor temperate pasture or micro-swards in indoor controlled environment. Outdoor grazing environments inevitably introduce some level of unpredictable and variable background noise that can readily interfere with the acquisition and analysis of chewing and biting signals. We aimed therefore to deal with commonly encountered levels of such noises by combining passive isolation (directional microphones with isolation material) and basic signal processing.

2. The algorithm

The design goal was the achievement of an algorithm that can combine high performance for detection and classification of sound events with low computational cost, which is a necessary condition to allow real-time execution of the algorithm in portable embedded systems. To achieve this goal, time-domain instead of transformed-domain (frequency, time–frequency) analysis was implemented to avoid high computational load of signal analysis.

2.1. General description

Signals associated with an exclusive chew (Fig. 1a), composite chew-bite (Fig. 1b) or exclusive bite (Fig. 1c) have readily distinguishable properties.

Therefore, the shape, maximum intensity and duration of sounds were isolated to discriminate among the bites, chews and chew-bites. The shape of a jaw movement is characterized by changes in both the intensity and sign of the envelope slope (Fig. 1). The sign (either positive or negative) of the envelope slope changes one or two times for chews and bites and more than two times for composite chew-bites. The three jaw movements also produce sounds with distinguishable maximum intensity that remains low for chews and high for bites, and changes from low to high for composite chew-bites. Finally, bites, chews and composite chew-bites, have a defined duration, which is shorter for chews and bites and longer for composite chew-bites (Fig. 1).

Sound properties were then used by the algorithm to complete two successive tasks, event detection and event classification, respectively. For the detection task, the algorithm detects the region of the sound envelope that shows the occurrence of a possible jaw movement. This detection is carried out through the identification of characteristic peaks in the sound envelope using an adaptive threshold. For the classification task the algorithm uses a simple set of rules to compute and compare the shape, intensity and duration of a detected event to a given threshold value.

For implementation purposes, the completion of the two tasks can be thought as a set of five successive stages, where the first four stages are used to complete the event detection task, while the event classification task is performed during the last stage, as follows.