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Surface electromyography segmentation and feature extraction for ingestive behavior recognition in ruminants

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ABSTRACT

This work presents a method to identify the ingestive behavior in ruminants using Surface Electromyography (sEMG) of the masseter muscle. The main hypothesis tested is whether the rumination and food eaten can be recognized from sEMG signal features using machine learning techniques. Also, a novel segmentation technique was explored and applied to automatically subdivide the chewing movement signal. Seven classifiers were evaluated using eight features extracted from the signal and combined into five sets. The three scenarios investigated were: differentiation between rumination and grazing (IR), food identification for four different foods (FC) and both situations combined (FCR). The segmentation window size effect on the accuracy was also investigated. We found an accuracy over 70% for IR and FC and nearby 60% for FCR using a Multilayer Perceptron Neural Network (MLP-NN). Highlighted features were the Cepstrum coefficients (CEPS) and the signal Wavelength (WL). Segments between 600 and 1000 ms proved to be suitable. The segmentation technique and the proposed scheme are reliable for application although there is room for improvement.

1. Introduction

Ruminant animals spend part of their day feeding and ruminating, which is a fundamental process to maximize digestion. The feeding behavior of ruminants is essential for the animal well-being and for disease detection (Geers, 1994). Measuring ingestive behavior parameters is a challenge, and indirect methods have been applied. Therefore, it is important to develop systems able to collect, process and analyze suitable information to identify and classify feeding and rumination patterns.

The available literature describes a wide variety of systems to inspect the ingestive behavior. Current methods comprise the measurement of physical parameters such as chewing frequency, distinction between chews and bites and feed intake. These methods apply electronic devices like jaw displacement transducers, halter switches, strain sensors, jaw balloons with integrated pressure transducers, gnathometers, accelerometers, RFID (Radio-Frequency Identification) ear tags and acoustic systems (Andriamandroso et al., 2016).

Recent research uses accelerometer and Quadratic Discriminant Analysis (QDA) in the classification of grazing, standing and walking behavior of sheep (Barwick et al., 2018). Noseband pressure sensors attached on halters (Braun et al., 2015; Kröger et al., 2016; Zehner et al., 2017) have been used to count bites, measure feeding and rumination time automatically besides estimating intake of cows (Leiber et al., 2016). Acoustic systems achieved a strong correlation with rumination time (Byskov et al., 2014) and recognition rates approaching 90% using an algorithm to classify bites, chews and chew-bites patterns (Chelotti et al., 2018).

Likewise, Pegorini et al. (2015) studied the Fiber Bragg grating sensors to monitor the biomechanical forces, allowing the identification of material textures via artificial neural networks. Experiments in cattle distinguished five patterns in the chewing process with an overall accuracy of 94%. However, the method is invasive, since the sensor must be fixed in the jaw bone.

The surface electromyography (sEMG) of the masseter muscle emerged as a reliable method to estimate feeding time of individual dairy cows (Büchel and Sundrum, 2014) and chew counting (Campos et al., 2016). Therefore, it is a potential tool for ingestive behavior

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research, since valuable information about sensory properties of food were successfully accessed through sEMG of human facial muscles (Kemsley and Defernez, 2012). The identification of rumination and feed classification using non-invasive sensors is a challenge not achieved so far.

Electromyographic data can be used as a method for motor patterns recognition (Oskoei and Hu, 2007). The classification involves three steps: feature extraction, feature selection and pattern recognition. Feature extraction is a technique which reduces the raw sEMG signal into representative features known as a feature vector (Phinyomark et al., 2013). The classification accuracy depends on the correct selection of the features (Oskoei and Hu, 2007). The feature vector must keep useful information while disregarding irrelevant ones, such as noise components (Zardoshti-Kermani et al., 1995), achieving dimension reduction. The feature selection step aims to choose which features better represents the proposed model. In the pattern recognition step a classifier assigns the input (feature set) to a correspondent output label.

The present study aimed to test the hypothesis that rumination and the category of feed eaten by ruminants can be recognized by the masseter muscle electromyographic data of the chewing activity. We applied several classifiers and feature vectors found in the literature. The effect of the signal processing, such as the frequency range of the filters and segmentation window size, was evaluated in order to adjust the optimal parameters. Three scenarios evaluated the classification accuracy for each feature set: distinction between rumination and grazing, food identification and both situations combined.

2. Materials and methods

2.1. Instrumentation

Surface electromyography (sEMG) data was acquired by the biological signal evaluation kit ADS1298ECG-FE (Texas Instruments®), an analog front-end module with programmable gain instrumentation amplifiers (PGA) where the conditioning circuit converts the analog raw signal into 24-bits digital data using a Delta-Sigma analog-to-digital converter (ADC). A Digital Signal Processor (DSP) sends the acquired data to a computer. Each analog input has an Electromagnetic interference (EMI) filter with Electrostatic discharge (ESD) protection. The instrumentation system used in this present study is shown in Fig. 1. Bipolar electrodes, attached to the masseter muscle to record the single-channel sEMG, were connected to the measuring board by shielded cables. For reference purposes, a signal feedback was applied on a non-related point. Lithium polymer (LiPo) batteries powered the system.

2.2. Animals and experiment procedure

The experiment used three castrated male goats (*Capra hircus*, 265 ± 50 days old, weighing an average of 35.9 ± 2.3 kg). The reason for choosing goats is because of their docile behavior, ease of handling and their availability on the experimental station. The study was approved by the Ethics Committee on Animal Use (CEUA) of the Federal University of Technology - Paraná (UTFPR), Protocol No. 2015-002. Each animal was housed for 15 h before the tests and deprived of food to ensure that all animals would eat when offered. After this period, the masseter region was shaved, cleaned and the surface electrodes attached, each electrode positioned 1 cm apart, lined up with the masseter fiber and centered on the muscle belly. The jaw end was chosen as the neutral point for the reference electrode. The electrodes were replaced every evaluation as signal quality reduces as the gel dehydrates (Searle and Kirkup, 2000).

The feeds were offered in turfs inside wooden boxes to create an environment where the animals could eat ad libitum. Data collection occurred while the animals were still eating or until consumption of the upper portion of the turf was achieved. The grasses offered were oatgrass (*Avena Sativa L.*), ryegrass (*Lolium multiflorium*), Tifton 85 (*Cynodon dactylon*) and Tifton 85 Hay. To simulate a free grazing condition no concentrate feed was offered, as this is the main production system in Brazil. After the feed was removed, animals were allowed to ruminate. Data collection remained up to the end of the rumination periods. The extent of the feeding and rumination period was not controlled as each animal spent different periods for each activity. On average feeding and rumination sampling periods lasted 180 ± 63 and 114 ± 44 seconds, respectively.

2.3. Signal processing

2.3.1. Sampling and signal filtering

The frequency of interest for sEMG is the 10–500 Hz band (Phinyomark et al., 2012). Therefore, a sampling rate of 1 kHz encounters the Nyquist-Shannon requirements.

The sEMG signals were digitally filtered *a posteriori* to select the desired band and eliminate 60 Hz overtones from the electrical power network noise. The high-pass filter cutoff frequency remained fixed at 10 Hz in order to remove motion artifacts and the low-pass filter cutoff frequency was set under examination.

2.3.2. Segmentation

Biopotential signals are non-stationary waveforms in a relative large scale regarding the intrinsic time-varying properties of the neural system (Tong et al., 2007). The decomposition of the signal into stationary or quasi-stationary intervals is difficult because the time series segmentation is not easily elucidated. Several methods have been attempted, such as segmentation based on the onset detection (Xu et al., 2013) and sample entropy (Micó et al., 2010). The onset segmentation is a well-known technique for sEMG segmentation, however it requires

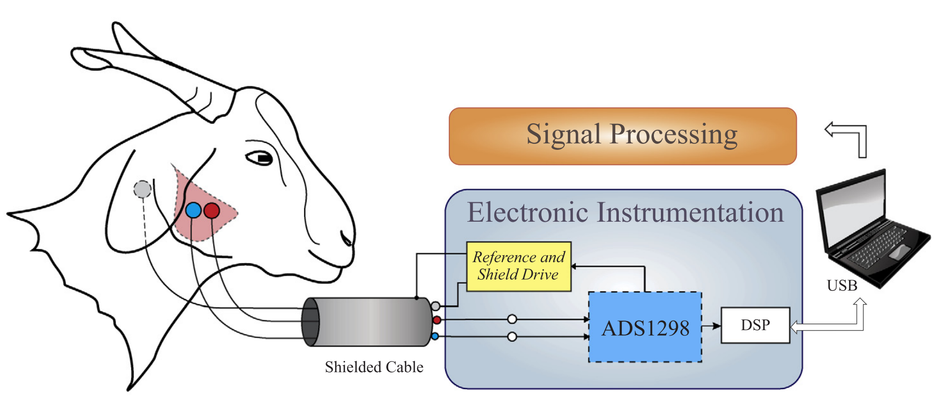

Fig. 1. Complete instrumentation and signal acquisition system. Bipolar electrodes record the muscle potential, which are converted to digital data and sent to a computer.