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Technical note

Non-intrusive real-time breathing pattern detection and classification for automatic abdominal functional electrical stimulation

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ABSTRACT

Abdominal Functional Electrical Stimulation (AFES) has been shown to improve the respiratory function of people with tetraplegia. The effectiveness of AFES can be enhanced by using different stimulation parameters for quiet breathing and coughing. The signal from a spirometer, coupled with a facemask, has previously been used to differentiate between these breath types. In this study, the suitability of less intrusive sensors was investigated with able-bodied volunteers. Signals from two respiratory effort belts, positioned around the chest and the abdomen, were used with a Support Vector Machine (SVM) algorithm, trained on a participant by participant basis, to classify, in real-time, respiratory activity as either quiet breathing or coughing. This was compared with the classification accuracy achieved using a spirometer signal and an SVM. The signal from the belt positioned around the chest provided an acceptable classification performance compared to the signal from a spirometer (mean cough (c) and quiet breath (q) sensitivity (Se) of $Se^c = 92.9\%$ and $Se^q = 96.1\%$ vs. $Se^c = 90.7\%$ and $Se^q = 98.9\%$). The abdominal belt and a combination of both belt signals resulted in lower classification accuracy. We suggest that this novel SVM classification algorithm, combined with a respiratory effort belt, could be incorporated into an automatic AFES device, designed to improve the respiratory function of the tetraplegic population.

1. Introduction

An injury to the cervical (neck) region of the spinal cord can cause paralysis affecting all four limbs, known as tetraplegia. People with tetraplegia also have paralysis or severe impairment of the respiratory muscles, resulting in reduced respiratory function. Associated respiratory complications are a leading cause of rehospitalisation for this patient group [1]. Functional Electrical Stimulation (FES), the application of a train of electrical pulses to a motor nerve causing the associated muscle to contract, can be used to make paralyzed muscle contract [2]. The application of FES to the abdominal muscles, known as abdominal FES (AFES), has been shown to improve the respiratory function of people with tetraplegia [3–5].

Gollee et al. [3] suggest that to maximize effectiveness, AFES for a quiet breath and a cough should be applied at different points in the breathing cycle, using different stimulation intensities. They suggest that quiet breaths should be stimulated at the start of exhalation, to support exhalation and avoid interfering with an inhalation, while coughs should be stimulated during glottal closure (between the end of inhalation and the start of a cough exhalation) in order to build up intrathoracic pressure, with a higher level of stimulation than a quiet breath. This earlier and greater degree of stimulation for a cough is aimed to increase intrathoracic pressure and aid cough generation. To enable the correct level of stimulation to be applied at the correct point in the breathing cycle, an automatic AFES algorithm must be capable of using data from an inhalation to differentiate between a quiet breath and cough in real-time. Gollee et al. [3] used the signal from a spirometer to identify a cough based on the inhalation flow rate and a quiet breath based on a cross-correlation algorithm. This system required manual setting of threshold values on a session by session basis. We have previously shown that the signal from a spirometer can be used with a maximum likelihood classifier for accurate real-time breathing classification [6]. This program required manual feature selection for each subject. For clinical use, it would be desirable to minimize manual intervention (e.g. threshold or feature selection) during setup.

Support Vector Machines (SVMs) are a statistical learning technique for binary classification problems with a good classification performance compared to other classifiers [7]. They require minimal operator intervention, making them a suitable alternative to the solutions outlined above.

A spirometer is typically combined with a full face mask which is uncomfortable and intrusive, leaving the user unable to eat, drink or verbally communicate while in use. Replacing a spirometer with

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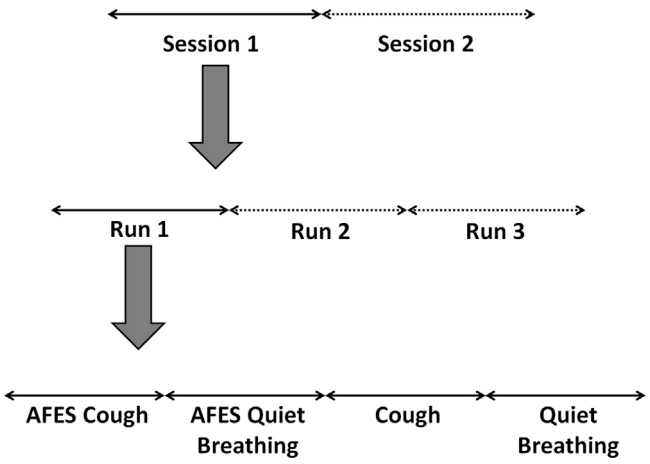

Fig. 1. Data collection protocol showing two sessions, split into three runs, with each run containing a period of AFES assisted and unassisted quiet breathing and coughing.

a less-intrusive sensor would make an AFES system considerably more practical. Non-intrusive respiratory effort belts are commonly used to detect sleep apnea following offline breathing pattern analysis [8]. In a single subject feasibility study, Gollee et al. [9] report that respiratory effort belts may be suitable for real-time breathing pattern detection. This suggests that they may provide a suitable non-intrusive signal for breathing pattern classification.

The aim of this study is to develop an SVM classification algorithm capable of classifying respiratory activity in real-time, with minimal operator intervention, using the signal from a non-intrusive sensor.

2. Methods

Ten able-bodied participants (6 males, age 27.6 ± 5.2 years (mean $\pm$ std)) were recruited and asked to attend two sessions. The study was approved by the local ethics committee and conformed to the declaration of Helsinki. All participants gave written informed consent.

2.1. Data collection protocol

The data collection protocol is summarized in Fig. 1. Experimental sessions included runs consisting of six coughs and one minute of quiet breathing, with and without the support of AFES. The order of these four breath types within each run was randomized, with each breath type following directly one after the other. Each run was repeated three times per session, separated by a rest period of approximately two minutes. The session was repeated after a period of approximately seven days.

The data recorded during the two sessions were combined for each participant. Data sets containing all of the cough data or all of the quiet breathing data were then created for each sensor.

2.2. Equipment and signal pre-processing

The participant's respiratory activity was recorded using a spirometer (Microloop, Micromedical, UK), connected to a full face mask (Hans Rudolph Inc., KS, USA), and with two non-intrusive respiratory effort belts (Piezoelectric belts, ProTech, USA), one positioned around the abdomen, at the umbilicus, and the other positioned around the front of the chest, at the sternum. The signal from the spirometer provided magnitude and direction of respiratory flow. The respiratory effort belts measured the stretch velocity at the chest and abdomen, respectively, which is directly related to the flow obtained using the spirometer.

The respiratory effort belts were connected to a custom amplifier and interfaced with a laptop computer via a 16-bit data acquisition card (NI DAQCard 6036E, National Instruments, USA), while the spirometer was connected via a RS232 interface. Data was recorded in the Simulink modeling environment (The Mathworks, USA) using custom-made blocks to enable real-time data acquisition at a sample rate of 50 Hz. The belt signals were high pass filtered to remove signal bias (1st order butterworth, cut off frequency 0.04 Hz). The spirometer signal was low pass filtered to remove high frequency noise (8th order simple moving average filter, cut off frequency 2.7 Hz).

2.2.1. Stimulation system

A neuromuscular stimulator (RehaStim v1, Hasomed, Germany) was used to stimulate the abdominal muscles bilaterally using four channels. Stimulation was applied via surface electrodes (33 mm $\times$ 53 mm rectangular, PALS, Axelgaard, USA) placed over the rectus abdominis and external oblique muscles on both sides of the body. Stimulation was automatically triggered at the start of each exhalation, defined as the moment when the spirometer signal crossed zero from a negative (inhalation) to positive (exhalation) value, and applied for a duration of 1.5 s for a quiet breath and 1 s for a cough. Bi-phasic current controlled stimulation pulses were applied at a frequency of 30 Hz. Stimulation current was adjusted on a channel by channel basis for each participant (with a pulsewidth of 100 μs) until a visible contraction was observed (range 10–60 mA for all participants), with this current remaining fixed for the remainder of both sessions. Stimulation pulsewidth was varied between 100 and 150 μs within each session to account for muscle fatigue. A custom LabVIEW (National Instruments, USA) interface, integrated with Simulink, was used to adjust the stimulation parameters.

2.3. Support Vector Machine

Features, extracted from each inhalation of the pre-processed data from each sensor, were used to train an SVM. For the spirometer the start of inhalation was defined as the moment when the signal crossed zero from a positive to a negative value. For both respiratory effort belts, the start of inhalation was defined as two consecutive negative samples, preceded by three non negative samples, where the previous zero crossing was the end of inhalation. The opposite logic was applied to detect the end of inhalation. Due to the high signal to noise ratio (achieved using the filtering techniques described in Section 2.2) these methods were found to be robust enough to minimize false positive detection. The features from a subset of approximately 50 cough and 100 quiet breath inhalations, together with information indicating whether the data represented a quiet breath or a cough, were used to train the SVM on a participant by participant basis. After training, the SVM was used to classify all of the breaths recorded from the participants who were not used to train the SVM as either a quiet breath or a cough. This was achieved using features extracted from each inhalation. The classification structure is explained in further detail in this section.

2.3.1. Feature extraction

Initially a total of 28 features, extracted from both the time and frequency domain, were considered as classifier inputs. To select features which were different in cough and quiet breathing, the following method was applied: the features values were extracted from the spirometer signal for all participants, and a Wilcoxon signed-rank test was performed. Those features which were found to be statistically significantly different ($p < 0.05$) for a quiet breath and a cough were then selected, resulting in 21 features (listed in