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Movement onset detection in various positions for state-based myo-control scheme

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ABSTRACT

Myoelectric prostheses offer great potential of rehabilitation for amputees. However, a main drawback toward this achievement lies in the control algorithms, which are unable to reliably translate the user's intention to the articulators (prosthesis motors) in an intuitive fashion. This study is part of an on-going project, to develop an alternative approach for myoelectric control, by de-correlating the pattern recognition classes and the actual position of the hand. It focuses on movement onset detection of two degrees of freedom from the hand and wrist complex, in various positions. With 6 channels of surface electromyogram (sEMG) mounted on the forearm, 4 healthy subjects were instructed to perform random sequences of movements with low level of contractions without returning to the rest position. A detection method was developed using a reference buffer and the energy variations in the sEMG. The results show that accurate detection of the movement onset can be achieved regardless of the actual position of the hand within a reasonable delay. This onset detection method is the first step toward a state-based control scheme for myoelectric control. Further work will use this detection method to trigger a classification algorithm and determine the target of the movement.

INTRODUCTION

The surface electromyograms (sEMG) can be non-invasively recorded from the skin surface, and represent the activity of the muscle fibres in the surrounding area. They are easy to acquire, and since they have shown to be an efficient way to control powered prostheses [1], they attracted great interest in the past decades. The state of the art for multi-function prostheses is mainly based on the pattern recognition approach. A large variety of algorithms [2-3] have been investigated for both movement classification and hand/wrist angles estimation, both showing very promising performance [4-5]. However, the pattern recognition approach assumes that different types of motion can be associated to distinguishable and consistent signal patterns in the surface EMG. This assumption, which can be true in very controlled laboratory settings, could be challenged in more realistic conditions. This is one of the main gaps between the academia state-of-the-art and industrial state-of-the-art.

Various commercial powered prostheses are actually available for upper limb amputees; however their control scheme is rather basic due to the lack of reliability of the more advanced methods. They mainly allow controlling two degrees of freedoms, with an unintuitive switching method, for example co-contraction, to switch between the articulated degrees of freedom (DOF).

The aim of this study is to reproduce the performance of such switch based algorithm, without the limitation and restrictions of the co-contractions. A state-based algorithm is being developed providing the control of one degree of freedom at a time, but offering a more natural approach when switching between the different articulated DOFs. This state-based control scheme relies on two main algorithms: the switch detection and the target decision.

The following of this paper introduces the switch detection algorithm and reports its performance on movement onset detection in various positions of the hand and wrist.

METHODS

Subjects

Four healthy subjects (3 males, 1 female) participated in the experiment. All subjects gave their informed consent prior participation to the experiment, and the procedures were approved by the local ethics committee.

Procedures

The experiment focused on 2 degrees of freedom (DoF) of the hand and wrist: Supination/Pronation of the forearm, and Closing/Opening of the hand, as these are the articulated DOFs of the commercial prosthesis the project is working on. Six pairs of electrodes (Ambu® Neuroline 720 01-K/12, Ambu A/S, Denmark) were mounted around the dominant forearm, equally spaced, one third distal from the elbow joint. The EMG data were recorded in bipolar

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derivations, amplified with a gain of 2000 (EMG-USB2, OT Bioelectronica, Italy), filtered between 10 and 750Hz, and sampled at 2048 Hz. The reference electrode was placed on the non-dominant forearm. Each experiment consisted of five runs, each performed with a different reference contraction (rest, forearm supinated, forearm pronated, hand closed, hand opened). For each contraction the subject was instructed to maintain the current position, release any previous contraction, and perform the newly instructed contraction at a low force level (~10% MVC). Each run was 2 minutes long and the order of the contractions was randomized. The subject was asked to move at preferred speed, and to keep the contractions for 3 seconds. Five-minute long breaks were observed between runs to minimize fatigue. No feedback was given to the subject to regulate the position or force but visual validation of by experimenter was performed. The wrist and hand kinematics were recorded with a motion capture system (Qualisys Track Manager, Qualisys AB, Gothenburg, Sweden) and 8 ball shaped markers were placed on the subject forearm and hand.

Detection algorithm

The detection algorithm was developed to deal with a continuous stream of data. It is based on a data buffer storing the recent data (i.e. the last 2500ms without positive detection, if available) recorded, and a last event detection time. For each new window (i.e. 40ms), a reliability factor is computed determining how likely the sEMG signal within the current window are in fact a part of a different state than the current one in the reference buffer. This reliability factor is computed according to two main components:

- The time elapsed since the last event detection
- The variance increase in channels between the reference buffer and the current window.

The last event time is the last time a potential switch in the EMG signal has been detected (i.e. reliability factor > 20%). If the previous window had a low reliability factor, the last event time is set as the beginning of the current window.

The time elapsed since the last event was used to avoid false switch detection due do sEMG variability during contractions. A percentage of reliability was computed according to this time value using a time function f_{time} plotted in Fig. 1. This function uses a time base value (i.e. 200ms). This value represents the minimum length to get the maximum reliability factor.

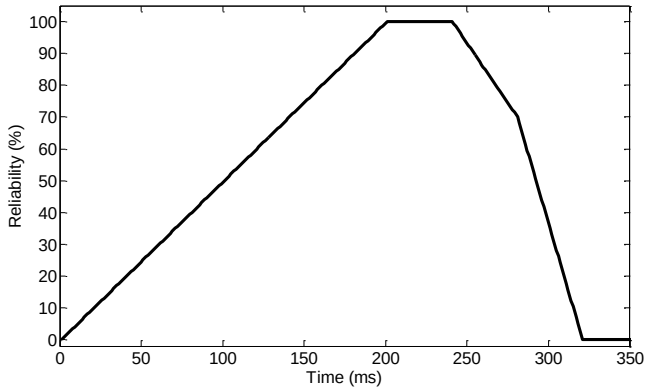

Figure 1: Representation of the time function f_{time} with a time base of 200ms.

To evaluate the variations in the signals compared to the reference state, the data buffer was divided in two parts: the data before the last event time (DBE) and the data after the last event time (DAE). The variation between the DBE and DAE was computed according to the Eq.1. If the left hand side of Eq.1 was larger than 1, the variation coefficient was set to 1 in order to keep its value between 0 and 1:

$$C_{variation} = \frac{1}{N} \sum_{channels} \frac{var(DAE)}{F \times var(DBE)} \quad (1)$$

where N is the number of channels, and F is the coefficient defining the minimum ratio to obtain the maximum value (i.e. F=3 means that the maximum value is reached as soon as the variance ratio is superior to 3).

The final reliability factor was computed as the product of the time component and the variation component, as in Eq.2

$$C_{reliability} = f_{time}(T) * C_{variation} \quad (2)$$

where T is the time since the last event.

The runs were analysed separately as the recordings are not continuous between runs. For each run, the data were down sampled to 1 kHz, and divided into non-overlapping windows of 40ms to simulate the online stream of data. The detection algorithm was run for each window, and a reliability factor for switching state was obtained for each window. The final decision on the detection of a switching event was made by threshold, requiring a reliability value of 80%.

RESULTS

The results for each run were: a true positive rate, a number a false positive per minute, and a latency value for each positive detection. The validation of the detection was done using the motion tracking data. An expected event was placed after each contraction instruction, at the onset of the recorded motion (~10% variation).

Fig.2 illustrates the results of one run

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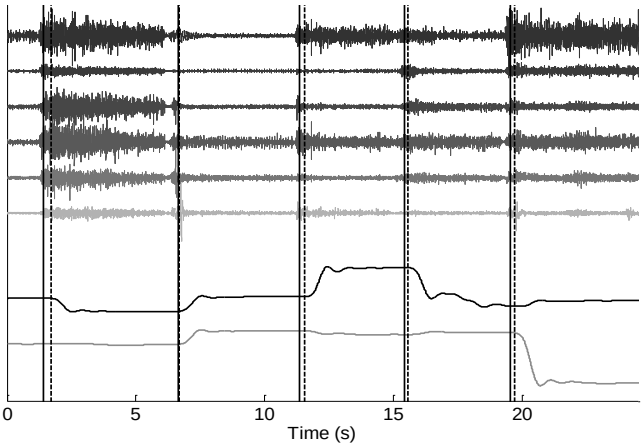

Figure 2: Detection result from one run during 24 seconds. The upper part shows the different sEMG channels. The lower two signals shows the angles from the motion capture system (angle between the fingers and the hand in black, angle between the wrist and the elbow in grey). The solid vertical lines are the detection from the algorithm, the dashed vertical line are the expected events using the motion capture data.

Table 1 summarise the results from all the subjects. It shows that the developed algorithm succeed to detect in average 93% of the performed contractions, maintaining the number of false positive at one per 2 minutes. Although the variability is quite high, the reported latency is in average of -130ms.

Table 1: Detection results by subjects

Subjects	True Positive rate (%)	False Positive (events/min)	Latency (ms)
Subject 1	0.93+/-0.07	0.4+/-0.8	-170+/-190
Subject 2	0.94+/-0.13	0.8+/-1.2	-220+/-200
Subject 3	0.90+/-0.08	0.5+/-0.4	-110+/-310
Subject 4	0.94+/-0.05	0.3+/-0.3	-20+/-410
Average	0.93+/-0.08	0.5+/-0.7	-130+/-290

DISCUSSION

The results of this study shows that the developed algorithm allows to detect more than 90% of the switches performed during the experiments while maintaining a false positive rate of 0.5 per minute.

In addition, the latency reported shows that in average the contraction can be detected prior to the movement. This ensure that the system under development can be responsive enough to be usable in real-time. The variability observed in latency is mainly related to the variation in reference positions. Indeed from a hand in open position with a low level of contraction towards the hand close contraction, the first part of the movement is executed by relaxing the muscles, thus in the first part of the movement there is no increase in the sEMG channels, delaying the detection.

Finally, this detection algorithm is meant to be part of the state-based control scheme. A detection in the sEMG does not imply a movement of the device, as the observed signals will have to correspond to one of the recorded target. Future work will investigate the performance of the entire state-based control scheme, using this detection method as well as the currently under development target detection method. It is expected to provide a more natural and progressive control scheme, yet reliable and clinically applicable.

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