CLASSIFICATION OF TRANSIENT MYOELECTRIC SIGNALS FOR THE CONTROL OF MULTI-GRASP WRIST-HAND PROSTHESIS

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ABSTRACT

Decoding the neurophysiological signal generated by voluntary arm movements is one of the major challenges in rehabilitation engineering. The most investigated approach for hand prosthesis control is the continuous pattern recognition of myoelectric signals. However, this is based on the assumption that repeated muscular contractions produce consistent patterns of steady-state myoelectric signals. Notably, it is the initial, transient, phase of such signals that was shown to contain a deterministic structure. Here we investigated if both wrist and hand intended movements could be decoded from the transient phase of the myoelectric signal. Twelve healthy individuals performed one of four grasps and of five wrist movements simultaneously (20 combinations). Albeit the performance in recognizing both movements simultaneously was poor, the offline data analysis showed the feasibility of implementing a sequential wrist-hand embedded controller based on the transient phase.

INTRODUCTION

Individuals with a below-elbow amputation maintain part of the 18 extrinsic muscles that originally served the fingers and wrist. The electromyogram (EMG) recorded from these muscles can, in theory, be used to control a variety of motor functions in upper limb prostheses. Remarkably, the clinical state-of-the-art controller is still the two-state amplitude modulation controller proposed by Bottomley back in the '60s, [1]. In this controller, a single pair of agonist/antagonist muscles controls the opening and closing of the prosthetic hand. However, this scheme cannot differentiate between different muscular patterns pertaining to different hand movements, and, accordingly, cannot be used to control multiple grasps of a dexterous prosthesis intuitively.

An alternative approach is *pattern recognition,* as first proposed by Finley and Wirta in 1967, [2]. This technique is based on the premise that amputees can activate repeatable and distinct muscular contractions for each class of desired motion and that the associated EMG patterns can be identified and used to control the prosthesis accordingly. In this framework, Englehart and colleagues pioneered the development of *continuous* classifiers [3]–[5] that still represent the state of the art.

Remarkably, the assumption that repeated muscular contractions produce repeatable patterns of steady-state EMGs is weak. In fact, the steady-state EMG has very little temporal structure (it is mostly a random signal) due to the active modification of recruitment and firing patterns needed to sustain the contraction [6], [7]. For these reasons, time-averaged, compound statistical properties have to be extracted from the EMG signals before classification. To further improve the reliability of the latter, low pass filtering techniques (e.g. majority voting, velocity ramp or confident-based rejection) are usually applied to the output of the continuous classifiers [4], [8], [9].

While investigating the properties of the EMG at the onset of muscle contraction (the *transient*), Hudgins and colleagues observed a substantial degree of structure in the signals of upper arm muscles [10]. This observable structure was reported by others [11], and suggests a consistent orderly recruitment of motor units between contractions [7]. In our previous work, we exploited the transient EMGs generated during hand grasps/gestures (lateral, cylindrical, tri-digital grasp and hand open) to identify the intended movements using a simple representative classifier (i.e. the SVM). We demonstrated that the transients contained predictive information about the intended grasp, [12]. In this work, we investigated the possibility to extend the proposed method to the classification of both hand and wrist movements. We evaluated offline the performance of such a system in solving different classification problems, assessing its ability to operate with sequential or simultaneous wrist-hand movements. As the latter was not deemed sufficiently robust, the former was ported in a real-time system for a qualitative assessment.

MATERIAL AND METHODS

Twelve healthy subjects (age 26 ± 2.63 years old, 7 males, 10 right-handed) took part in the experiments after giving their informed consent.

Subject were asked to sit on a chair with the elbow flexed at 90 degrees on a table to limit the participant's fatigue during the test (Figure 1A). Eight EMG signals were sampled at 2 kHz (band-pass filtered at 10-900 Hz) using a signal amplifier (EMG-USB2+, OT Bioelettronica, Turin, Italy) and eight bipolar self-adhesive electrodes placed around the forearm (Figure 1B). In the described position, the subjects were asked to simultaneously perform one of the 20 possible combinations of two movements, involving: the hand (rest, lateral, tri-digital and cylindrical grasps) and the wrist (rest, flexion, extension, pronation and supination).

A custom-made graphical user interface was developed to help the subjects during the execution of the trials driving the type and timing of requested movements of both hand and wrist (Figure 1C). The interface also allowed the participant to pause the procedure in the interval between two movements to recover from fatigue, if required. Following the graphical hints in the interface, the participants were asked to: (i) execute a simultaneous movement of hand and wrist, (ii) keep the contraction for 3 seconds, (iii) move back to the initial resting condition. Three series of the 20 combinations were performed. Each series included five repetitions of each combination, for a total of (3 series × 5 repetitions × 20 combinations) 300 movements per participant. The order of movements was randomized among series.

The EMG signals were processed to extract the mean absolute value (MAV) on 100 ms windowed data, by sliding the observation window on a single sample basis. The obtained signal was then down-sampled at 20 Hz and processed to extract the onset of muscle contraction through an onset detection algorithm (ODA). The ODA was applied to the derivative of the MAV. Specifically, for every class, the median peak of each series was calculated. Then, the minimum peak across series was set as the threshold.

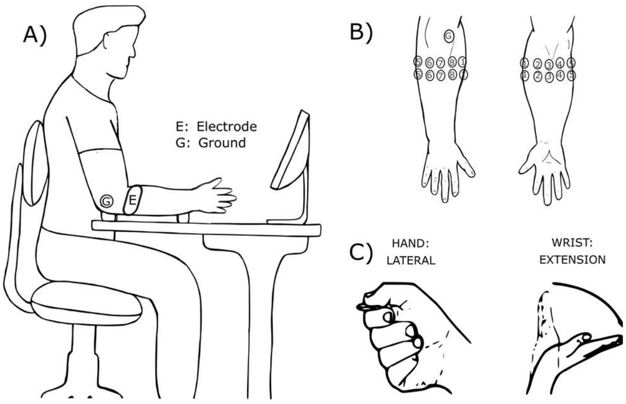

Figure 1: A) Experimental Setup. Participants were sitting in front of a monitor with the elbow flexed at 90 °.
B) Electrodes were uniformly distributed around the proximal part of the forearm. C) The Graphical User Interface informed the user on the next simultaneous movements to perform.

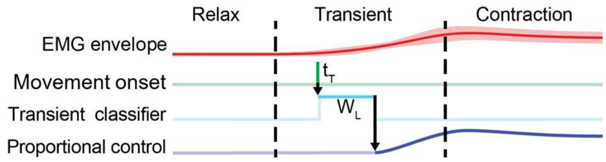

Figure 2: Transient EMG classifier concept. Once the transient detection algorithm (ODA) identifies an onset (at t_T), the transient window (W_L) is recorded and classified.

In analogy with Kanitz et al. [12], after each detected onset, a different number of temporal MAV samples was extracted and provided to the classifier in order to establish which window length (W_L) allowed an optimal trade-off between classification accuracy and delay (Figure 2). Specifically, W_L ranged between 0 and 300 ms in steps of 50 ms (corresponding to 1,…,7 MAV samples). Using these features, a linear SVM classifier was trained and cross-validated for each subject, splitting the available data in 5 folds, assigned to each fold based on the order of repetitions of each series (leave-one-repetition-out approach). The classifier was tested in solving three different problems (P1-P3) with growing complexity:

P1. Recognizing grasps or wrist movements separately with two dedicated classifiers (four hand and five wrist classes).

P2. Recognizing grasps or wrist movements separately with one eight-class classifier.

P3. Recognizing grasps or wrist movements when performed simultaneously (20-class classifier).

A solution to P1 was searched to test if the results obtained in classifying the grasps [12] could be extended to wrist movements as well. Solving P2 would enable a sequential control of a robotic hand-wrist prosthesis. Finally, we also considered the more complex problem of recognizing hand and wrist movements performed simultaneously (P3).

Concerning the porting of the algorithm, an online classifier was implemented as suggested in Kanitz et al. [12].

RESULTS

The experimental recordings lasted for around one hour per participant, including the setup preparation. Results for all the addressed problems showed that the classification accuracy increases with W_L (Figure 3). This was expected as the longer the W_L, the more information is available to the

Table 1: Confusion matrix for the problem 2 for grasps and wrist movements (W_L = 200 ms)

Actual class	*Lateral*	*Pinch*	*Cylindrical*	*Extension*	*Flexion*	*Pronation*	*Supination*	*Rest*
Lateral	**142 (79.33%)**	10 (5.59%)	17 (9.50%)	3 (1.68%)	0 (0%)	0 (0%)	6 (3.35%)	1 (0.56%)
Pinch	5 (2.81%)	**140 (78.68%)**	5 (2.81%)	6 (3.37%)	4 (2.25%)	9 (5.06%)	9 (5.06%)	0 (0%)
Cylindrical	13 (7.22%)	2 (1.11%)	**147 (81.67%)**	1 (0.56%)	1 (0.56%)	7 (3.89%)	9 (5.00%)	0 (0%)
Extension	2 (1.11%)	2 (1.11%)	0 (0%)	**150 (83.33%)**	0 (0%)	6 (3.33%)	15 (8.33%)	5 (2.78%)
Flexion	2 (1.11%)	4 (2.22%)	1 (0.56%)	0 (0%)	**161 (89.44%)**	5 (2.78%)	6 (3.33%)	1 (0.56%)
Pronation	1 (0.56%)	3 (1.67%)	1 (0.56%)	8 (4.44%)	0 (0%)	**146 (81.11%)**	18 (10%)	3 (1.68%)
Supination	5 (2.81%)	1 (0.56%)	1 (0.56%)	5 (2.81%)	2 (1.12%)	11 (6.18%)	**151 (84.33%)**	2 (1.12%)
Rest	2 (1.11%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (0.56%)	**177 (98.33%)**
	Grasps Accuracy: 79.88%			*Wrist Accuracy: 84.68%*				
								Overall Accuracy 84.59%

classifier. However, W_L longer than 150 ms (or four MAV samples) improved the performance only slightly.

In general, the classification accuracy reached a plateau around W_L = 150 ms. Specifically, the performance did not improve significantly (Friedman test) for W_L > 150 ms for P1 and P2, and for W_L > 100 ms in the case of P3 (Figure 3). By comparing the different tested problems, accuracies for P3 were generally lower (58.86 % for W_L = 300 ms) than those obtained for P1 and P2 (93.33 % for W_L = 300 ms). Considering P2, the inclusion of wrist movements did not have a critical impact on the overall performance when compared to P1 (93.33 % vs 89.54 %, respectively). Specifically, wrist movements and grasps were classified with an overall accuracy of 84.68 % and 79.88 % (Table 1), respectively. In fact, wrist movements were classified more accurately than grasps (Table 1). This held true also for P1 and P3 (not shown).

Following the results mentioned above, the optimal solution was considered the one from problem P2. Thus, a single eight-class classifier was implemented and tested online. The outcomes from the online implementation and feasibility test are preliminary and qualitative in nature. Following a short training, consisting of 15 repetitions for each of the eight classes, the participant was able to use the online controller (supplementary video S1[1]).

DISCUSSION

To summarize, we claim that forearm EMGs patterns at the onset of a contraction contain predictive information about both upcoming hand and wrist movements. Moreover, this information can be used for real-time control of a wrist-hand prosthesis.

The transient EMG approach uses only the data contained in a short window associated to the onset of muscle contraction, which is known to contain a deterministic structure [10], [11]. The advantage of this approach is that classification is only necessary when a transient window is detected by the ODA, making the entire system less prone to errors. In addition, when errors occur, it is comparatively simple for the user to abort the ongoing grasp attempt and start anew. Importantly, since the contraction *precedes* the actual movement, the response time of the *transient* classifier is faster than that of a conventional continuous classifier.

Results from P1 complement the ones from our previous work [12] showing that the control strategy based on transients maintains very good performance also if applied to wrist movements (Figure 3).

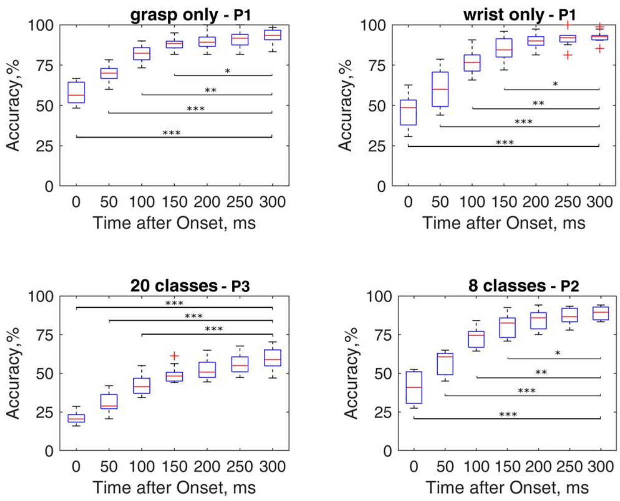

Figure 3: Results for considered problems as a function of the window length. The statistical analysis was performed with the Friedman test (*: 0.05 ≥ p > 0.01; **: 0.01 ≥ p > 0.001; ***: 0.001 ≥ p).

[1] https://drive.google.com/open?id=1WC2aWKbbIyQHhGwmHk0DMj1SfWQ02rIm

P3 represented the most challenging case, a 20-class classification problem involving simultaneous wrist and hand movements. The effort needed to acquire such a complex training set and the results obtained do not justify the use of a transient-based classifier for simultaneous hand-wrist control. The significant reduction in performance observed here with respect to P1 and P2 suggests that the information contained in the transients does not simply sum up constructively when more than a single anatomical district is involved in the movement. Several other groups also tried to investigate alternative methods for the simultaneous control of multiple degrees of freedom (DoF), but failed when the number of classes to be recognized increased above three or four [13], [14].

On the other hand, in P2 we analysed a standard eight-class classification problem that allows non-simultaneous hand-wrist movements. In this case, the performance were sufficiently good and only slightly worse than the ones obtained in P1. Notably, as analysed from Liu et al. [15], grasps and wrist movements are almost independent during normal reach-to-grasp tasks. In other words, a grasp is executed only after the wrist is already positioned. This perspective makes it feasible and natural to control the DoFs of a wrist-hand prosthesis in sequential manner. A result of these considerations is a reduction of control complexity.

This work has some limitations: (i) here we performed an offline analysis of the designed classifier and a qualitative evaluation of the online system (one subject case). It would be desirable to better evaluate the latter case, ideally including functional tests. (ii) We showed data acquired exclusively from healthy participants. An extension to amputee subjects is necessary to confirm the clinical usability of the algorithm. (iii) P3 would need a very extensive training phase (i.e. 15 repetitions × 20 classes = 300 trials) that is not compatible with a prosthetics application. We mitigated the problem with the continuous classifier (i.e. 15 repetitions × 8 classes = 120 trials), but the training phase is still quite demanding. Thus, the training phase part should be optimized to limit the number of repetitions needed to train each class. (iv) As a preliminary evaluation, we used a single feature: the MAV of the EMG. However, it is known that multiple time-domain features improve the accuracy of classification [16]. Future works will involve the introduction of new features, oriented particularly to an embedded real-time application.

Finally, we generalized the approach from our earlier work, extending the number of classes to include wrist movements. At the moment, a quantitative assessment of the real-time performance of a transient-based EMG controller are ongoing with both healthy and amputee subjects. Albeit we excluded the possibility to simultaneously control wrist-hand movements, we argue that a sequential control strategy based on the transient phase of the EMG could provide a natural and intuitive way to control a prosthetic device.

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