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The DOI of the final edited version of this paper is: doi: 10.1097/JPO.0b013e3182524cce

Manuscript accepted for publication on JPO, 2012

THE EFFECTS OF WEIGHT AND INERTIA OF THE PROSTHESIS ON THE SENSITIVITY OF EMG PATTERN RECOGNITION IN RELAX STATE

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ABSTRACT

For transradial amputees, the muscles in the residual forearm physiologically employed for flexing/extending the hand fingers, are the most appropriate targets, for multi-fingered prostheses control. However, once the prosthetic socket is manufactured and fitted on the residual forearm, the EMG recorded from the stump might not be originated only by the intention of performing finger movements, but also by the muscular activity needed to sustain the prosthesis itself. In this work, we show –on eight healthy subjects wearing a prosthetic socket emulator– that (i) variations in the weight of the prosthesis, and (ii) upper arm movements significantly influence the robustness of a traditional classifier based on k-nn algorithm, causing a significant drop in performance. We demonstrate in simulated conditions that traditional pattern recognition do not allow the separation of the effects of the weight of the prosthesis because a surface recorded EMG pattern due only to the lifting or moving of the prosthesis is misclassified into a hand control movement. This suggests that a robust classifier should add to myoelectric signals, inertial transducers like multi-axes position, acceleration sensors or sensors able to monitor the interaction forces between the socket and the end-effector.

INTRODUCTION

To myo-electrically control a multi-fingered dexterous prosthesis –like e.g. the recently marketed RSL Steeper BeBionic[1], the iLimb[2] or research prototypes like the SmartHand[3], VU Hand[4], or the

DARPA RP 2009 *Intrinsic Hand*[5] it is necessary to map electromyographic (EMG) signals corresponding to different muscle contractions to the different existing degrees of freedom (DoF) of the hand using a suitable algorithm. Myoelectric control techniques can be divided into two categories: *non pattern recognition* and *pattern recognition* based[6,7]. Non-pattern recognition control, includes proportional control, threshold control, onset analysis and finite state machines. These schemes have a simple structure and have been mostly deployed in ON/OFF or proportional control. In particular, in proportional control the strength of muscle contractions controls the prosthesis speed or force. This type of control scheme has received widespread clinical acceptance but provides reduced functionality, typically limited to only one or two DoF. In research labs, sophisticated algorithms implement pattern recognition[6]. This is based on the condition that amputees can voluntarily activate repeatable and distinct EMG signal patterns for each class of motion, which in turn, can be mapped to physiologically appropriate prosthesis commands.

A multitude of groups have implemented and designed controllers using different combinations of extracted features and classification methods (for a review of the EMG processing techniques refer to the work by Oskoei and Hu[7]) showing the feasibility of controlling dexterous prostheses. These systems have been demonstrated usually through offline pattern recognition[8-10], through algorithms suitable for real-time processing and classification[11-13], but only in few instances, with actual real-time classifiers[14-16] or directly controlling robotic hand finger movements[17, 18]. Results in this field are improving increasingly but slowly, and research is mainly focusing on real-time signal processing techniques, new pattern recognition algorithms (e.g. Hargrove et al.,[19, 20]) and other computational issues.

However, all previous research is related to experiments performed in controlled laboratory environment, with the stump of the subjects lying in a **comfortable position**: i.e. with no moving limbs/stumps. It is foreseen that future systems should be able to deal with bio-signals coming from a

free-to-move residual limb; in such case, the main open problems are: source localization (muscle motion problems), skin impedance changes, removal of artefacts, prosthesis donning/doffing, and separation of intention from other physical factors (like fatigue, stump posture, etc.). In transradial amputees, the (up to) 19 extrinsic muscles in the residual forearm which naturally are employed by unimpaired subjects for flexing/extending the hand fingers, are the most appropriate targets, for multi-fingered prostheses control. However, once the prosthetic socket is manufactured and fitted on the residual forearm, the recorded EMG might not be originated only by the intention of performing finger movements, but also by the muscular activity needed to sustain the prosthesis itself. Indeed, in contrast to a healthy forearm, for amputees, the actions caused by the weight of the prosthesis (payload and inertia while moving) are partially distributed on the muscles above the elbow (e.g. biceps-triceps), and partially on the forearm muscles; this being reinforced by the reaching posture of the prosthetized limb which is generally unnatural due to the lack of biomechanically correct wrist movements. Additionally, movements of the socket relative to the stump (caused e.g. by the inertia of the prosthesis when it is moved) might generate artefacts, i.e. involuntary signal variations. Traditional techniques do not allow the separation of such effects, therefore, an EMG pattern due only to the lifting or maintaining of the prosthesis can be misclassified into a hand control movement, as a consequence of a false positive.

To tackle this problem, the idea of a robust interface including EMG and inertial transducers (i.e. multi-axes position and acceleration sensors) for intuitive prostheses control was patented by Cipriani et al.,[21] and similarly, the adverse effects of limb position on pattern recognition control were investigated on healthy subjects and presented by joint research between the University of New Brunswick (UNB), Canada, and the Norwegian University of Science and Technology (NTNU)[22-25]. To our knowledge the first work that proposed to combine EMG signals with inertial information of the arm for hand gesture recognition, was carried out by Chen et al.,[26] although it was not meant for upper limb prosthetics control.

Within this exciting and newly-born framework, in the present paper, we demonstrate –on eight healthy subjects and emulated conditions– that (i) variations in the weight of the prosthesis, and (ii) upper arm movements weaken the robustness of pattern recognition. Results of this work, suggest a simple but effective strategy for the control of multi-fingered prostheses based on the monitoring of the prosthesis weight and upper limb posture. This paper extends preliminary data presented at the 2011 *Myoelectric Control/Powered Prosthetics Symposium*[27] and at the *IEEE Conf. of the Engineering in Medicine and Biology Society*[28]; compared to those works the novelties reside in a greater number of experimented subjects, in a different setup employing a prosthetic *socket emulator* (see definition below) that reduced the possibility of electrode artefacts, and the experimental tasks, and finally, in the feature set fed into the pattern recognition classifier.

MATERIALS AND METHODS

Eight able-bodied subjects (S1-S8; 4 male, 4 female, mean age 28 years old, standard deviation 5) naïve to EMG experiments, and all having a dominant right arm, took part in this study. Raw surface EMG data were collected employing the Noraxon TeleMyo 2400R (Noraxon, Scottsdale, AZ, USA) through a wireless unit (TeleMyo 2400T). Raw data were then acquired at a sampling frequency of 1.5 kHz, 1st order 10 Hz hardware high-pass filtered, 8th order 500 Hz hardware Butterworth low-pass antialiases filters, resolution of 12 bits, hardware gains of 1000, and stored for an offline analysis in MatLab environment. In order to investigate on individual finger classification eight channels were used to record myoelectric activity from the right-hand forearm muscles. Disposable Ag–AgCl surface electrodes in bipolar configuration with an inter-electrode distance of 20 mm were used. The electrodes were placed around the forearm, in a cuff fashion close to the elbow, at the position with largest muscle bulk (cf. Fig. 1). In this way superficial flexor and extensor muscles were recorded. The reference electrode was placed on the proximal part of the lateral epicondyle. Once connected to the electrodes, the cables of the EMG recording system were carefully held in place with a bandage, in order to avoid signal artefacts caused by movements of the arm during the experiments.

The experiments were divided into three phases with a 10 minutes break within phases, to allow relaxation. The first phase consisted of a traditional pattern recognition exercise (e.g. like those described in[11,18]), where subjects performed finger movement repetitions; this was aimed to assess the accuracy of a benchmark pattern recognition algorithm, under ideal conditions (i.e. lab-constrained). The subsequent two phases were carried out in order to assess the worsening effects of the weight of the hand prosthesis under **realistic** conditions. In particular, the effects of the payload were studied in phase two, and the effects of inertial while moving were investigated in phase three.

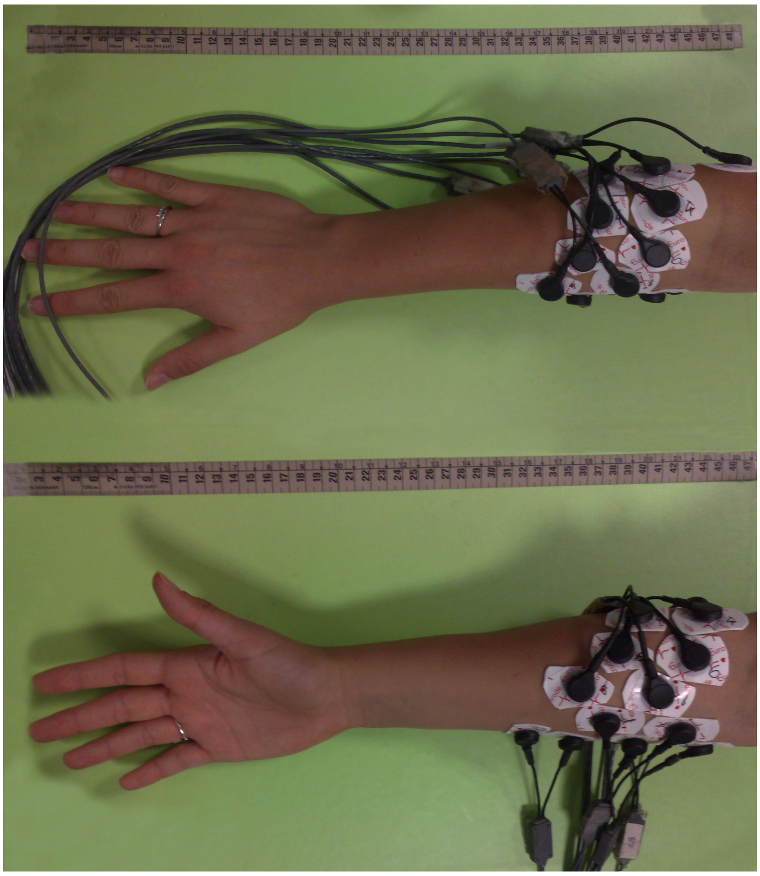

Fig. 1 Placement of the electrodes on the right hand forearm of one of the participants. Once connected to the electrodes the cables were carefully held in place with a bandage, in order to avoid signal artefacts caused by movements of the arm during the experiments.

Phase 1: Pattern recognition under ideal conditions

The participants were seated in front of a screen with their forearm resting on a pillow during this phase. The hand default posture allowed the extrinsic muscles to be totally relaxed, as visually inspected through the EMG recording system. Eight different movements were executed by the subjects in response to a written and pictorial cue on the screen and an auditory cue that depicted the movement to be reproduced. The movements consisted of flexions and extensions of the thumb and index fingers individually, of the middle, ring, and little finger as a group, of the long fingers (all excepting the thumb) as a group, and finally of a rest class making up **nine classes** in total. These movements would account for individual control of each degree of freedom of an advanced prototype like the VU- or the Smart-hand[3, 4]. Each movement was sustained for 3 seconds and a 3 second rest was given between subsequent movements. Two different datasets each consisting of 3 repetitions of each movement totalling 24 movements and the rest states were stored on a computer along with the intended class information.

A simple but effective classifier already used in our previous work was employed[18]. It consisted of a k-nearest neighbour (with k equal to 8) algorithm employing the Euclidean distance as the distance metric, the mean absolute value (MAV) and waveform length (WL) as feature set, and Principal Components reduction as preprocessing. For all subjects the first recorded dataset was used for training (hereafter calibration dataset) and the second for evaluation. The overall classification accuracy from one representing subject (S5) is shown in the confusion matrix in Fig. 2. The mean classification accuracy for all participants in the nine classes was fairly high: 73%± 8% (st. dev). What is really interesting here, is the classification errors for the relax state; these are reported in the first column of Table 1. Since they represented the baseline for the subsequent phases, it is worth underlining that they were significantly low for all subjects. It is also worth noticing that better classification accuracies are possible with more complex classifiers (as shown e.g. by Hargrove et al.,[19, 20]), or if the system is finely subjectively adjusted.

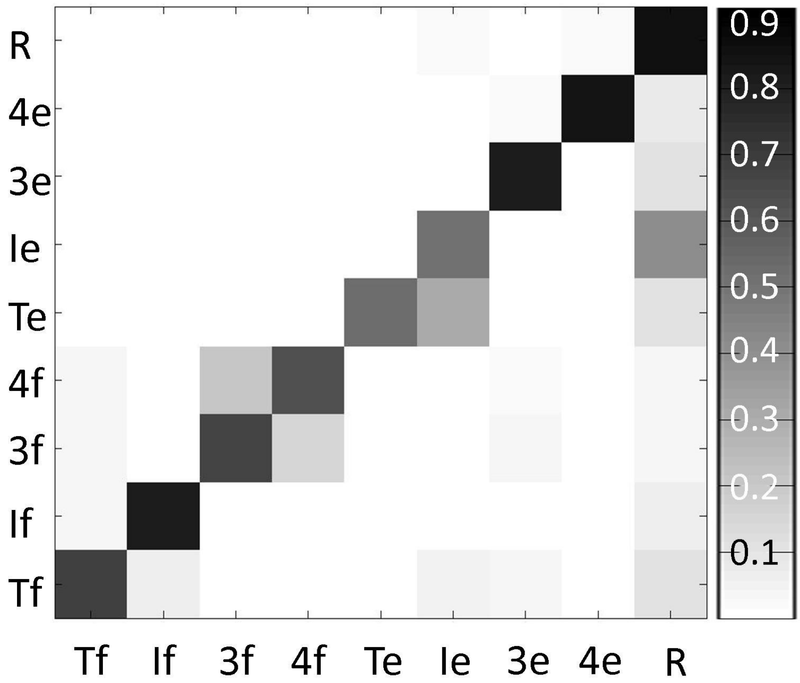

Fig. 2 Confusion matrix for one representative subject in which the Y axis represent the intended movements and the X axis represent the actual classified movements. Movement list: Tf: thumb flexion, If: index flexion, 3f: three finger (middle, ring and little) flexion, 4f: four finger (index, middle, ring and little) flexion, Te: thumb extension, Ie: index extension, 3e: three finger extension, 4e: four finger extension, R: relax. Figures are not shown for clarity.

Phase 2: Effects of Static Payload

In order to resemble the fact that transradial amputees wear a prosthetic socket usually rigidly connected to the elbow and hence cannot pronate/supinate the forearm, subjects during this second phase wore an orthopaedic rigid wrist brace, (hereafter called prosthetic socket emulator, cf. Fig. 3), that impeded forearm movements (i.e. wrist pronation/supination) and kept the hand always in a fixed –and relaxed– position. While placing the electrodes, particular attention was paid in order to avoid any physical interference between the prosthetic socket emulator and the electrodes. This precaution was taken to avoid signal artefacts caused by unpredictable, varying pressure of the prosthetic socket onto the electrodes, during the experiments.

Fig. 3 Orthopaedic wrist brace used in phase two and three of this study. A metal pin within the device (not shown in the picture) constrained pronation/supination of the arm and helped to keep the hand in a relaxed position. The device was short enough and did not interfere with the placement of the electrodes proximal to the elbow.

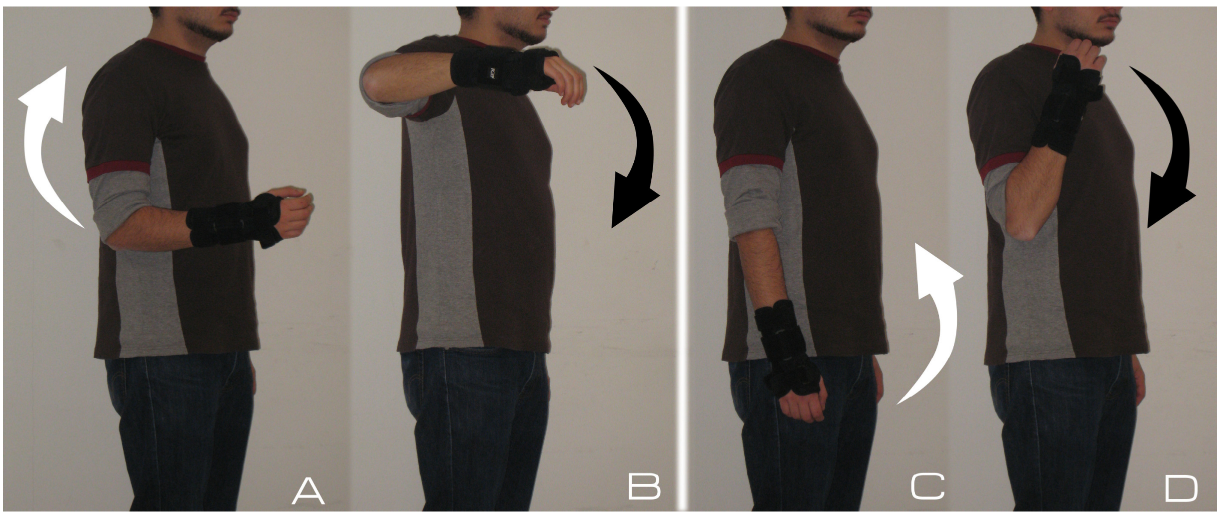

Fig. 4 Experimental protocols used in phase three of this study. Shoulder abduction/adduction movement (A-B) and the elbow flexion/extension (C-D). The postures depicted in pictures A and B were also used in the second phase of the experiments to assess the effects of weight.

Subjects were asked to maintain a static posture with their arm, while the endpoint of the socket emulator was cyclically loaded and unloaded with a mass (3 seconds loaded and 3 seconds unloaded, 10 to 15 times depending on the subject). Two static postures were tested, the first (posture A) with the arm attached to the body and the elbow forming a 90 degree angle (cf. Fig. 4A) and the second posture (posture B) maintaining the elbow flexion and abducing the shoulder until bringing the arm in line with it (cf. Fig. 4B). Theoretically in both postures the payload was not supported by forearm muscles (those involved in the grasp action), but by arm and shoulder muscles. Subjects were instructed to keep their forearm muscles always relaxed during the loading/unloading cycles. In the first posture 3 loads (10, 15 and 20 N) were tested; in the second posture just the 20 N load was used. This protocol aimed to imitate and investigate the effects on pattern recognition of the weight of the prosthesis acting with a certain lever arm on the prosthetized stump of a transradial amputee. The recorded EMGs were classified using as training data the calibration dataset recorded in phase one.

Phase 3: Effects of Inertia while Moving

Effects of inertia on the classification accuracy were tested in this third phase of the experiments. Subjects were asked to execute two kinds of movement not involving the forearm muscles: the first one was shoulder abduction/adduction (between postures A and B in Fig. 4A-B), the second one was elbow flexion/extension (between postures C and D in Fig. 4C-D). In both cases subjects were asked to perform cyclically (i) the first part of the movement (e.g. shoulder abduction), (ii) keep the position for N seconds, (iii) perform the second part of the movement (e.g. shoulder adduction) and (iv) keep this position for N seconds. Two different speeds were tested in two following sessions: first at slow speed (movement completed in around 2 seconds; N equal to 3 seconds), afterwards at a faster, physiological, speed (movement completed in 1 second; N equal to 2 seconds). Audio cues for an easier synchronization were delivered through earphones. In order to mimic the prosthetized condition a 0.5 kg mass was attached to the end of the socket emulator (the standard weight of an adult size prosthesis is around 0.5 kg indeed[1-2]). Subjects were instructed to keep their forearm muscles always relaxed, and the EMG signals while performing the movements were acquired and off-line classified using as training data the calibration dataset recorded in phase one.

RESULTS

Effects of Static Payload

Subjects were instructed to keep their hand relaxed during the loading/unloading cycles. Since the mass was ideally sustained by biceps and shoulder muscles (in posture A and B, respectively), the extrinsic muscles of the hand in the forearm were not supposed to be active. Instead, as hypothesized in the introduction the load was partially sustained also by the forearm muscles, of which activity led to the misclassification of the relax state. This effect is depicted in the temporal graph in Fig. 5 where a representative sample from subject 3 is shown (load: 20 N). The black line denotes the mean MAV among the 8 EMG channels, whereas the dots indicate classification errors as computed by the classifier (0: correct classification; 1: classification error). U and L intervals on the time scale denote the load and unload phases, respectively.

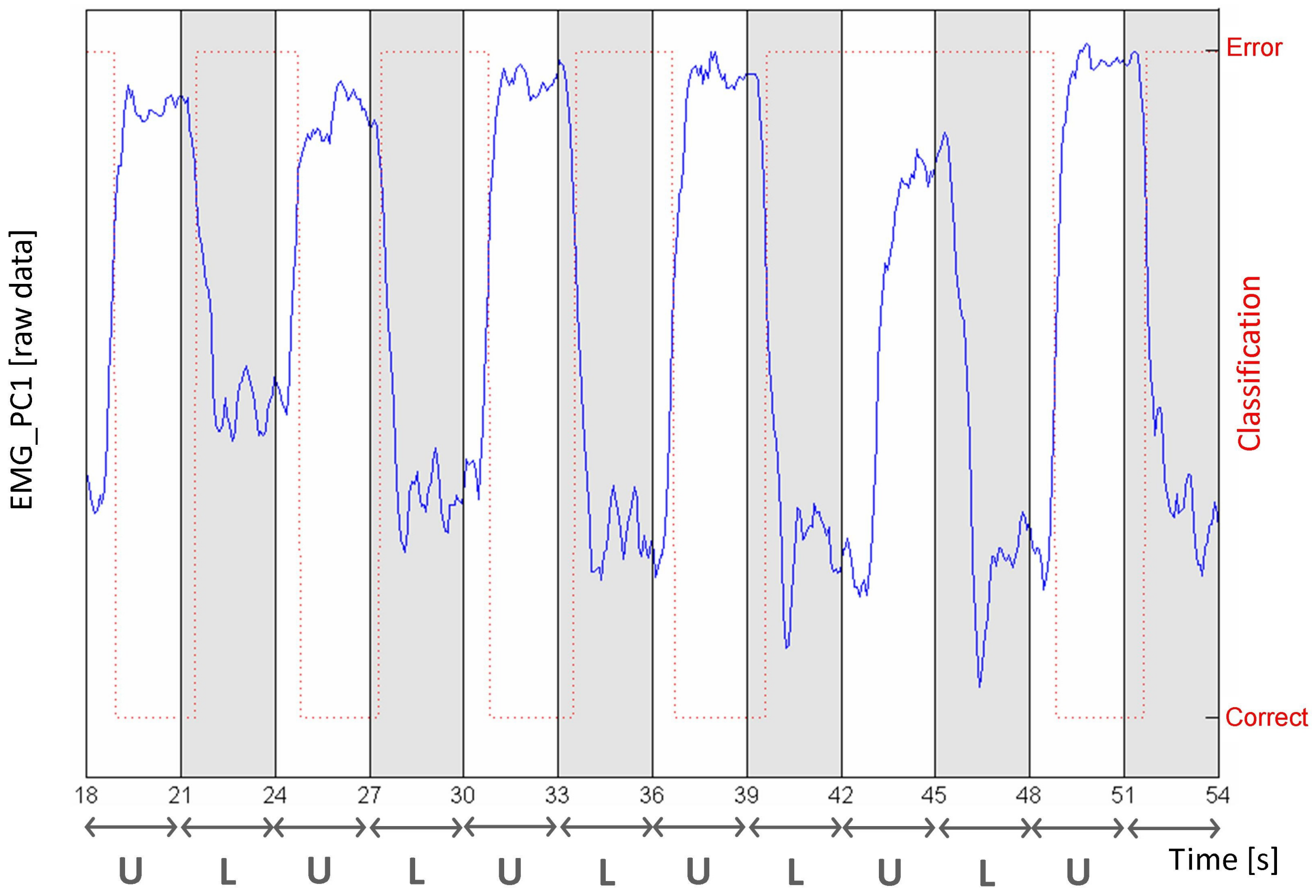

Fig. 5 EMG activity (first Principal Component; black trace) and classifier output (binary data; dotted trace) from Subject 3 during loading (L) and unloading (U) phases using the 15 N load.

This graph clearly shows the myoelectric activity variations causing the relax state to be misclassified every time the load was applied, and –almost always- properly classified once the load was removed. Table 1 shows the relax classification errors during the loading phases (grey windows in Fig. 5) included in the whole dataset, for all subjects in both postures tested (cf. Fig. 4A and B). The effects of the weight were highly subjective and also depended on the posture tested (either A or B). Few typical behaviours could be observed; for the first one, noticeable in subjects S1 and S6, the higher the load, the larger the classification error. For few subjects the classification error was not significantly affected by the variation of the load (e.g. S2, S3, S4, S5, S7, S8). In all cases, static loads yielded to a tremendous decrease in classification accuracy (worse for some subjects, e.g. S2, S3, S7, S8); by transferring this to the transradial amputee situation, a traditional pattern recognition algorithm would generate involuntary control commands every time the weight of the prosthesis changes (e.g. every time a new object is grasped).

Table 1: Classification errors of the relax state under ideal conditions and weight effects.

Subjects	**9 class – ideal conditions**	**Effects of Static Payload**			
		Posture A			**Posture B**
		10 N	**15 N**	**20 N**	**20 N**
S1	3%	21%	44%	50%	16%
S2	5%	98%	95%	97%	80%
S3	3%	80%	85%	68%	55%
S4	2%	40%	40%	45%	9%
S5	1%	42%	52%	48%	13%
S6	1%	15%	44%	53%	55%
S7	0%	98%	99%	99%	56%
S8	1%	92%	78%	86%	76%
Mean ± st. dev.	2% ± 2%	61% ± 33%	65% ± 23%	61% ± 21%	55% ± 27%

Effects of Inertia while Moving

A representative temporal graph of EMG activity (MAV) and classifier output stream, while subject no. 3 was executing the movement at slow speed, is shown in Fig. 6. Similarly to the other test, the plot shows that the myoelectric activity causes the relax state to be misclassified every time the forearm moves (from C to D, cf. Fig. 4C-D), and sometimes even when it is maintained flexed (posture D).

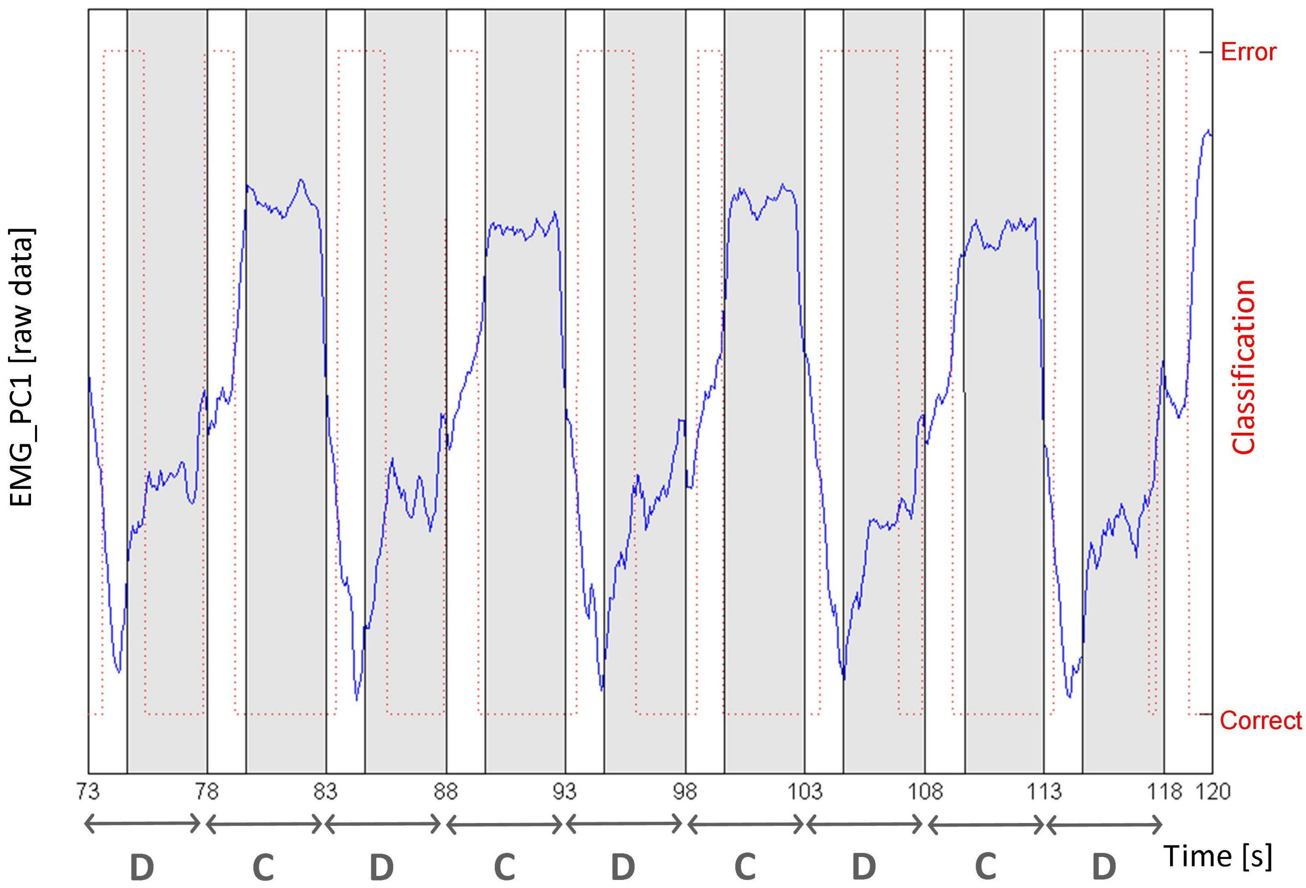

Fig. 6 EMG activity (first Principal Component; black trace) and classifier output (binary data; dotted trace) during flexion-extension of the elbow by Subject 3. C and D time intervals represent the windows when the elbow was flexed and extended, respectively (as shown in Fig. 4 C and D).

Table 2 quantifies the relax classification errors resulting from the whole dataset for the subjects performing the two movements, at two speeds, during the dynamic (light-grey windows in Fig. 6; lasting 1 second after the cue for the fast movement or 2 seconds for the slow movement) and the static (dark-grey windows in Fig. 6; 2 seconds for the fast movement or 3 seconds for the slow movement) parts of the exercise. Overall, the classification errors are considerably high, and as presumed, usually greater in the dynamic part of the movement than in the static one. While the reason for the misclassification in the dynamic phase can be attributed to the effects of inertia on the classifier, the misclassification in the static phase is likely to be due to the 0,5 kg mass attached to the socket emulator. Interestingly the classification error in the shoulder movement (A-B) was lower in the fast exercise, than in the slow exercise. For the elbow movement, instead, fast or slow did not make a significant difference.

By transferring these effects to the prosthetized situation, a traditional pattern recognition algorithm would generate involuntary control commands every time the prosthesis is moved.

Table 2: Classification errors of the relax state under ideal conditions and movement effects.

Subjects	9 class – ideal conditions	Effects of Inertia while moving							
		Shoulder movement (A-B)				Elbow movement (C-D)			
		Slow		Fast		Slow		Fast	
		Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static
S1	3%	0%	0%	17%	7%	64%	53%	62%	55%
S2	5%	81%	56%	99%	99%	51%	72%	52%	61%
S3	3%	100%	100%	87%	81%	33%	45%	56%	37%
S4	2%	0%	0%	0%	0%	8%	1%	40%	32%
S5	1%	0%	0%	0%	0%	50%	43%	57%	54%
S6	1%	81%	48%	0%	14%	100%	64%	0%	8%
S7	0%	94%	84%	100%	100%	68%	54%	56%	61%
S8	1%	0%	14%	81%	37%	0%	8%	94%	51%
Mean ±st. dev.	2% ± 2%	81% ± 44%	48% ± 39%	17% ± 46%	14% ± 44%	51% ± 27%	53% ± 21%	56% ± 20%	54% ± 18%

DISCUSSION

The present study was carried out on a limited number of healthy subjects, and demonstrates that a controller based on traditional pattern recognition algorithms, can not be the appropriate solution for achieving individuated finger control of multi-fingered hand prostheses available today. This study was based on a k-nn classifier, but similar results could be achieved with different, more complex algorithms. In fact as demonstrated by Farrell and Weir with an extensive work on pattern recognition[29], that compared different feature-sets and recording techniques (targeted surface, targeted intramuscular, and untargeted surface electrodes), the fundamental requirement is the ability of the algorithm to accurately identify a pattern, regardless to which feature-set or recording technique is used. Other studies[11, 30] reached the same conclusions when dealing with individuated finger movements.

The large variability in the results across subjects can be explained by the experimental setup which was not based on targeted muscle recordings. Indeed, although the geometrical localization of the electrodes was standardized among subjects, the considerable differences between length and dimension of the forearms, fat tissue, and eventually anatomy, could not allow for a direct comparison between subjective results. For this reason, besides the few general considerations, it was interesting to show typical misclassification cases (cf. Fig. 5 and Fig. 6).

In order to remove the load and inertial effects of the prosthesis on the amputee's residual forearm, i.e. to obviate this clinical issue once the socket is fitted on the stump, one possible approach is to monitor the posture and movement of the prosthetized limb (this data could be easily computed by means of DoF sensors, having on board accelerometers and gyros along multiple axis) and/or monitor the interaction forces between the socket and the prosthesis (by means of multiple axis load cells). Such information could be used to compute the load and inertial force vectors which affect EMGs, and once modelled, such effects could be compensated by the controller.

Additional sensors monitoring the position of the limb, were also proposed and recently exploited by the joint research between UNB and NTNU[22-25], which carried out experiments similar to those presented in this study. In their work, they showed that the variations in limb position associated with normal use had a substantial impact on the robustness of EMG pattern recognition. Hence, as we suggest here, they proposed to solve the problem, they defined *limb position effect* by including in the training set of the classifier an extra signal referred to the limb position measured by accelerometers; this technique successfully reduced the classification errors. In our opinion the main limitation of those studies[22-25], carried out with normally limbed subjects, was that they did not include in the experimental setup a device that sustained the hand, thus allowing full relaxation of the recorded forearm muscles, i.e. what in this study is defined as *prosthetic socket emulator*. In their experiments, in the different positions of the limb tested, the hand was always kept in line with the forearm, i.e. not relaxed. Therefore, the adverse *effects of limb position* on EMG pattern recognition they report, are in our opinion likely to be caused by the forearm muscles activity needed to sustain the hand in the various positions, which would not happen in the case of amputees, as there wouldn't be a hand to sustain. Although we believe that the main causes of misclassification, in the case of amputees would not be the so called *effects of limb position*, but as shown in this paper, the *actions caused by the weight* of the prosthesis which are partially distributed on the forearm/stump muscles, the approach of monitoring the limb posture to improve daily-life robustness of pattern recognition proposed by those studies[22-25] is exactly the same suggested by this work.

Specifically, we envision a classifier which output is inhibited every time the acceleration of the prosthesis (or of the socket) overcomes a certain threshold, and that automatically changes the mapping between EMG signals to the existing DoFs in the hand, based on the posture of the limb and on the interaction forces between the prosthesis and the socket. A system like this could successfully tackle the misclassification of traditional pattern recognition due to inertia while moving and static payload[21].

ACKNOWLEDGEMENTS

This work was supported partially by the Ministero dell'Istruzione, dell'Università e della Ricerca, under the FIRB 2010 - MY-HAND Project prot. RBFR10VCLD, and partially by the European Commission, under the WAY Project (EU-FP7-ICT-288551).

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