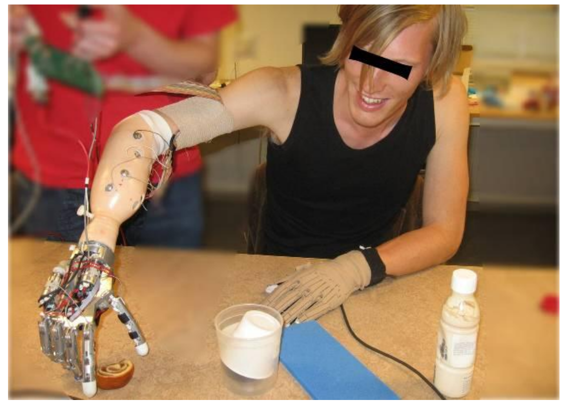

Fig. 1 Amputee reaching an object wearing SmartHand. The unnatural reaching posture of the arm caused by the lack of the 3 degrees of freedom of the wrist/forearm is clear from this picture.

# PRELIMINARY STUDY ON THE INFLUENCE OF INERTIA AND WEIGHT OF THE PROSTHESIS ON THE EMG PATTERN RECOGNITION ROBUSTNESS

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## ABSTRACT

For transradial amputees, the muscles in the residual forearm naturally 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. In this work, we preliminary show –on 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. We show in simulated conditions that traditional pattern recognition systems do not allow to separate 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 RSLSteeper BeBionic [1] or research prototypes like SmartHand [2] or the Vanderbilt University Hand [3], 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. In research this is frequently done through pattern recognition based techniques [4]. Since the 1960s, various groups have designed controllers using different combinations of extracted features and classification methods (for a review of the EMG processing techniques refer to [5]) showing the feasibility of controlling dexterous prostheses. These systems have been demonstrated usually through offline pattern recognition [6]-[8], through algorithms suitable for real-time processing and classification [9]-[11], but only in few instances, with actual real-time classifiers [12]-[14] or directly controlling robotic hand finger movements [15], [15]. Results in this field are improving incrementally but slowly, and research is mainly focusing on real-time signal processing techniques, pattern recognition algorithms and other computing 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 (cf. Fig. 1), 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 an 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 (cf. Fig. 1). 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 to separate 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 recently patented by Cipriani *et al.*, [17] and similarly, the adverse effects of limb position on pattern recognition control were investigated on healthy subjects and presented by Scheme *et al.*, [17]. Within this framework, in the present paper, we preliminarily show –on three 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, although still preliminary, 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.

## MATERIALS AND METHODS

Three able-bodied subjects (two men and a woman aged 25, 27 and 27 years old, respectively) took part in this preliminary study. The dominant hand was the right hand for the first and third subject and the left one for the second subject. 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. Four channels recorded signals from superficial flexor muscles on the volar side of the forearm and four channels were placed on the superficial extensor muscles on the dorsal side of the forearm as shown in Fig. 2. The reference electrode was placed on the proximal part of the lateral epicondyle.

The participants were seated in front of a screen with their forearm resting on a pillow during the time of this experiment. The hand default posture allowed the extrinsic muscles to be totally relaxed, as visually inspected through

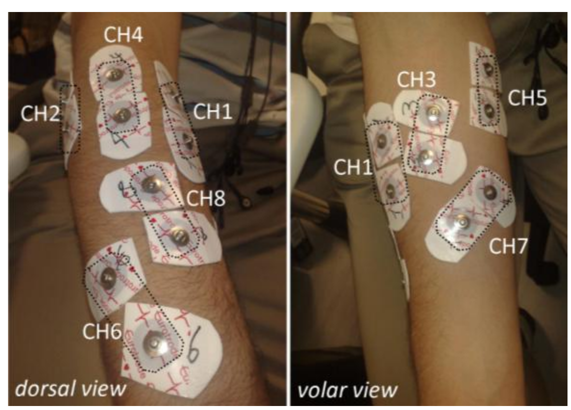


Fig. 2 Placement of the electrodes on the right hand forearm of one of the participants.

the EMG recording system. Ten 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 but the thumb) as a group and of thumb abduction, and finally of a rest class making up ten 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 [2], [3]. Each movement was sustained for 5 seconds and a 5 second rest was given between subsequent movements. Two different datasets each consisting of 3 repetitions of each movement totalling 27 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 [16]. It consisted of a k-nearest neighbour (with k equal to 8) algorithm employing the Euclidean distance as the distance metric and the mean absolute value (MAV) as feature set. For both subjects the first recorded dataset was used for training (hereafter calibration dataset) and the second for evaluation. The resulting classification accuracies are shown in the confusion matrices in Fig. 3. It is worth underlining that the classification accuracy for the relax state was 91%, 95% and 89% for the first, second and third subject, respectively. Two experiments –as detailed in the following sub-sections- were carried out in order to assess the worsening effects of the weight (i.e. payload and inertia while moving) of the hand prosthesis on a simple pattern recognition based control.

### Weight Effects

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 experiment wore a prosthetic socket emulator (cf. Fig. 4A-D), that impeded forearm movements and kept the hand always in fixed –and relaxed– position.

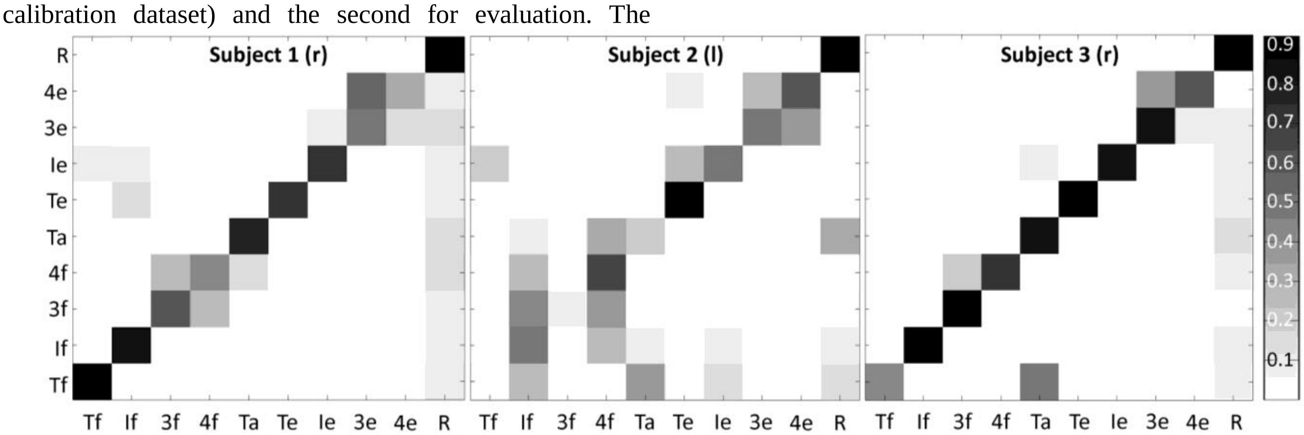


Fig. 3 Confusion matrices from the three participants. Movement list: Tf: thumb flexion, If: index flexion, 3f: three fingers (middle, ring and little) flexion, 4f: four fingers (index, middle, ring and little) flexion, Te: thumb extension, Ie: index extension, 3e: three fingers extension, 4e: four fingers extension, R: relax. The letter in brackets refer to the dominant hand.

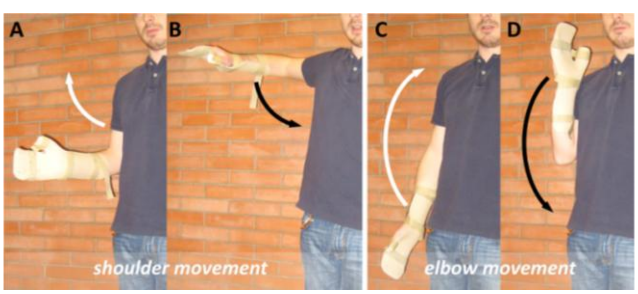


Fig. 4 Experimental protocols. Shoulder abduction/ adduction movement (A-B) and the elbow flexion/extension (C-D). The postures depicted in pictures A and B were also used in the weight effects experimental protocol.

Subjects were asked to maintain a static posture with their right arm, while the endpoint of the socket emulator was cyclically loaded and unloaded with a mass (3 seconds loaded and 3 seconds unloaded, 5 times). Two static postures were tested, the first (posture A) with the arm attached to the body and the elbow forming a 90 degrees 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.

Movement Effects

Effects of inertia on the classification accuracy were tested in this second experiment. 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 at physiological speed (i) the first part of the movement (e.g. shoulder abduction), (ii) keep the position for 3 seconds, (iii) perform the second part of the movement (e.g. shoulder adduction) and (iv) keep this position for 3 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.

## RESULTS AND DISCUSSION

Weight Effects

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, which activity led to misclassification of the relax state. This effect is depicted in the temporal graph in Fig. 5 where a representative sample from subject 2 is shown (load: 15 N). The black line denotes the mean MAV among the 8 EMG channels, whereas the red dots indicate the output class label computed by the k-nn classifier (label 5 corresponds to the relax class). U and L intervals on the time scale denote the load and unload phases, respectively.

The graph clearly shows the myoelectric activity variations causing the relax state to be misclassified every time the load was applied, and properly classified once the load was removed. Table 1 resumes the relax classification accuracies during the loading phases (grey windows in Fig. 5) included in the whole dataset, for the three subjects in both postures tested (cf. Fig. 4A and B). The effects of the weight were highly subjective and further investigations are hence required before being able to draft any conclusion. However, as a general preliminary remark, static loads yielded to a decreased classification accuracy (worse for subject 2 where EMGs were recorded from his non-dominant arm). 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).

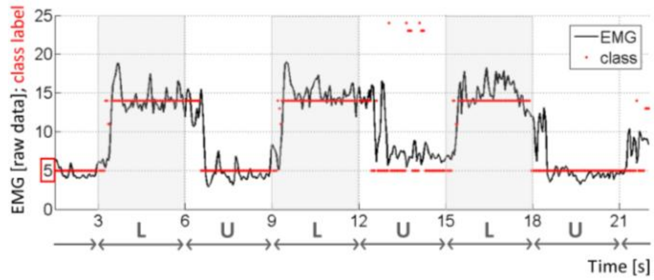


Fig. 5 EMG activity (black line) and classifier output (red dots) from Subject 2 during loading (L) and unloading (U) phases using the 15 N load.

Table 1: Classification accuracies of the relax state at different loads and limb postures

| | Posture A | | Posture B | |
|---|---|---|---|---|
| | *10 N load* | *15 N load* | *20 N load* | *20 N load* |
| Subject 1 | 100% | 89% | 20% | 12% |
| Subject 2 | 1% | 6% | 1% | 8% |
| Subject 3 | 100% | 98% | 44% | 4% |

Movement effects

A representative temporal graph of EMG activity and classifier output stream 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 is maintained flexed (posture D). In this case the activity might also be caused by artefacts due to cyclical peaks of pressure of the socket emulator on specific electrodes; this effect would still be present in the case of an amputee wearing a prosthetic socket, hence is of interest of this study.

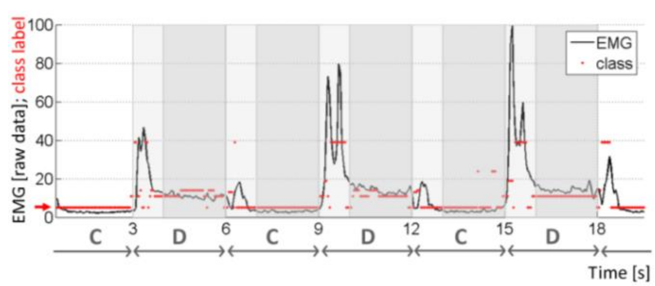


Fig. 6 EMG activity (black line) and classifier output (red dots) during flexion-extension of the elbow by Subject 2. C and D time intervals represent the windows when the elbow was flexed and extended, respectively (as in Fig. 5C and D).

Table 2 quantifies the relax classification errors resulting from the whole dataset for the three subjects performing the two movements, during the first second after the movement cue (light-grey windows in Fig. 6), and during the two subsequent seconds (dark-grey windows in Fig. 6). The former relates to the dynamic part of the movement, whereas the latter refers to the static phase.

The classification errors are considerably high, and as presumed, 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 and on the muscle-electrode interface (skin movement artefacts), the misclassification in the static phase is probably due the 0,5 kg mass attached to the socket emulator. By transferring this 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 with different movements

| | **Shoulder movement** | | **Elbow movement** | |
|---|---|---|---|---|
| | ***Dynamic*** | ***Static*** | ***Dynamic*** | ***Static*** |
| Subject 1 | 39% | 38% | 43% | 4% |
| Subject 2 | 15% | 12% | 45% | 19% |
| Subject 3 | 40% | 25% | 24% | 17% |

To obviate this clinical issue once the socket is fitted on the stump, i.e. to remove the load and inertial effects of the prosthesis on the amputee’s residual forearm, 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.

## ACKNOWLEDGEMENTS

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