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***Abstract*— A real-time pattern recognition algorithm based on k-nearest neighbours and lazy learning was used to classify, voluntary EMG signals and to simultaneously control movements of a dexterous artificial hand. EMG signals were superficially recorded by eight pairs of electrodes from the stumps of five transradial amputees and forearms of five able-bodied participants and used online to control a robot hand. Seven finger movements (not involving the wrist) were investigated in this study. The first objective was to understand whether and to which extent it is possible to control continuously and in real-time, the finger postures of a prosthetic hand, using superficial EMG, and a practical classifier, also taking advantage of the direct visual feedback of the moving hand. The second objective was to calculate statistical differences in the performance between participants and groups, thereby assessing the general applicability of the proposed method. The average accuracy of the classifier was 79% for amputees and 89% for able-bodied participants. Statistical analysis of the data revealed a difference in control accuracy based on the aetiology of amputation, type of prostheses regularly used and also between able-bodied participants and amputees. These results are encouraging for the development of non-invasive EMG interfaces for the control of dexterous prostheses**

***Index Terms*—Dexterous prosthesis, Electromyography (EMG), Pattern Recognition, Real-time control, Transradial amputation.**

I. Introduction

THE challenges towards a real neuro-controlled hand are in two areas: robotics and neuroscience. The problems researchers are facing are (i) how to develop a dexterous mechatronic hand with actuation and sensory features comparable to the human hand, and (ii) how to control this dexterity. Current battery powered hand prostheses are relatively simple mechanical hands or hooks activated by voluntary residual muscle contractions generating electromyographic (EMG) signals, superficially picked-up from the amputee's residual limb and properly decoded to control an intentional opening or closure [1]. In the past decades, knowledge of robotics has been extended to the field, so that several new designs including dexterous multiple degrees of freedom (DoF) and sensory equipped prosthetic hands have been developed and presented by researchers and manufacturers (for a review of such devices see [2]). Nevertheless one of the main impediments towards a massive clinical evaluation and their commercial exploitation is represented by the lack of a robust, reliable, and intuitive control interface, allowing dexterous control. While acquisition of invasive biosignals from the motor cortex may be suitable for tetraplegics [3], who have lost their ability to control the entirety of their upper limbs, and less invasive

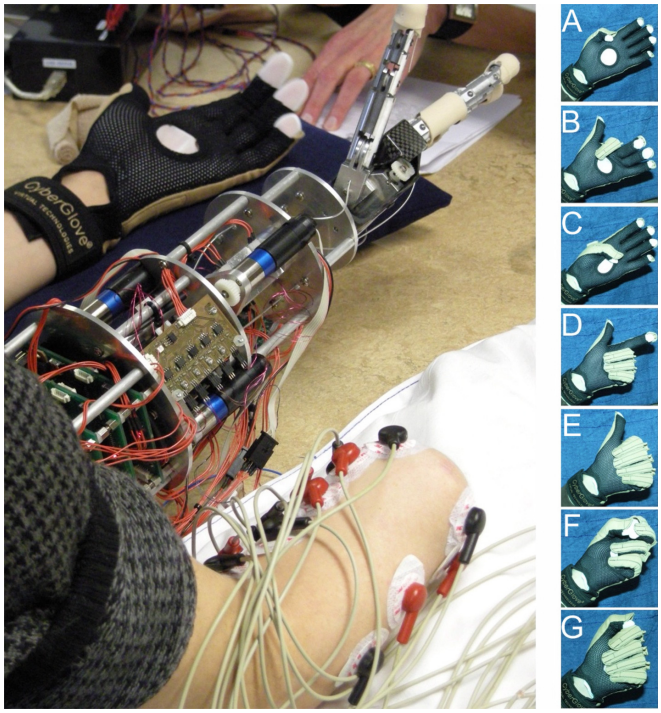

Fig. 1 Experimental setup. Left: the CyberHand prototype in a natural position from the participants' point of view. The stump lies in a resting position. Right: the seven movements included in the experiment. A is thumb flexion, B: index flexion, C: thumb opposition, D: middle, ring and little flexion, E: long fingers flexion, F: tridigital grip, G: lateral grip.

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techniques like the Targeted Muscle Reinnervation (TMR) procedure [4], or the implantation of neural interfaces in the peripheral nerves [5] may provide more accurate controllability, noninvasive biosignals such as surface EMG from a residual limb seem to be the most appropriate near term solution for transradial amputees. Besides, sophisticated human-machine interfaces like [4] and [5] still have to prove their effectiveness in a number of patients.

To myo-electrically control a dexterous prosthesis it is necessary to map EMG signals (corresponding to different muscle contractions) to the different existing DoFs using pattern recognition based algorithms [1], [6]. To this aim, 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 [6]) showing the feasibility of controlling dexterous prostheses. These systems have been demonstrated usually through offline pattern recognition [7]-[15], through algorithms suitable for real-time processing and classification [16]-[18], but only in few instances, with actual real-time classifiers [19]-[23] or directly controlling robotic hand finger movements [24].

Among these studies only a few investigated the possibility of controlling independent finger movements, or hand gestures [15], [16], [21], [24], while most considered wrist movements such as flexion/extension, pronation/supination, abduciont/adduction and sometimes hand closure/opening (all fingers simultaneously). Due to their gross nature, these movements are more reliably detected, with respect to finger postures or specific grips, but surely less intuitive if the aim is to control finger postures or particular grasps. However, as remarked by Tenore *et. al* [16] the greatest level of dexterity corresponds to achieving endpoint control of each individual finger, and this should be implemented with regards to the three key aspects of controllability, as Englehart and Hudgins identified in [18]: *accuracy* of movement selection, *intuitiveness* of the interface, and *response time* of the control system. Within this framework the problem of (i) real-time, (ii) accurate, and (iii) intuitive finger control for dexterous prostheses has been left open, and to our knowledge there is no previous research dealing with all these aspects simultaneously.

Our previous work showed preliminary data on the off-line pattern recognition of hand movements in a single transradial amputee performing different finger motion tasks [25]. This paper presents the first work on the simultaneous decoding of seven hand postures (finger movements) and real-time control of a robotic hand, performed by 10 participants using superficial EMG. Five of the participants were able-bodied and five transradial amputees, among which one had a congenital failure of formation. The proposed experiments were aimed at addressing two key objectives. The first objective was to understand whether it was possible to control in real-time, with reasonable accuracy the finger postures of a prosthetic hand, using superficial EMG and a *practical* classifier based on local approximation using lazy learning [26]. Therefore this study was to investigate the effect of visual feedback on the amputee, that is not possible with offline classifiers. The second objective was to verify the general applicability of such method, and therefore to assess statistical differences in the classification accuracies between participants and groups. Once the real-time controllability of the proposed system has been shown, we elaborate on the feasibility of making it portable for real clinical experimentation and evaluation in activities of daily living (ADL) and for future industrial exploitation.

II. Materials and Methods

A. Artificial Hand

A stand-alone version of the Cyberhand [27] was used (see Fig. 1) in the experiments. It is a right hand, with five underactuated fingers driven by six motors: five of which are employed for the independent flexion/extension of the fingers, and one for the abduction/adduction of the thumb (detailed description in [27]). Position sensors (encoders) and tendon tension sensors (able to measure the grasp force for each finger [28]) are integrated in the hand. Position control loops are embedded in a 8-bit microcontroller-based architecture and triggered by external commands from a standard RS232 bus. Therefore it is possible to drive each finger to a specific flexion posture by simply sending an appropriate position command.

B. EMG Real-time Pattern Recognition and Control

The pattern recognition system, slightly revised from the one presented in [29], is composed of (i) an eight channel bipolar EMG signal acquisition system, (ii) a data glove recording healthy hand joint positions, and (iii) a PC, running an application acquiring glove-data and EMGs, implementing pattern recognition algorithms based on *lazy learning* [26] and sending real-time control commands to the hand. Myoelectric signals collected from electrodes were filtered and amplified (2nd order band-pass filter, bandwidth 3-1000 Hz, Gain 5000 using NL824 amplifiers from Digitimer Ltd, UK) , sampled (at 10 kHz), and digitized (12 bits resolution) by a data acquisition board (DAS16/330, Measurement Computing). The data-glove (Cyberglove, Virtual Technologies) with 18 finger joint angle sensors, was fitted on the hand opposite to where EMGs are recorded; for amputees this was their intact hand (cf. Fig. 1). The purpose of the glove was to record reference positions to be associated with EMG recordings and to be used as position set-points for the artificial hand, as in [16], [29]-[31]. This was also a relatively simple way for identifying when the movement was actually performed, and for tracking and mapping EMG patterns to finger trajectories [16] when participants perform synchronously predefined movements with both their hands (or with their healthy and phantom hands). Therefore, the 18 glove joint-angles were mapped into 6 position control values (suitable for the 6

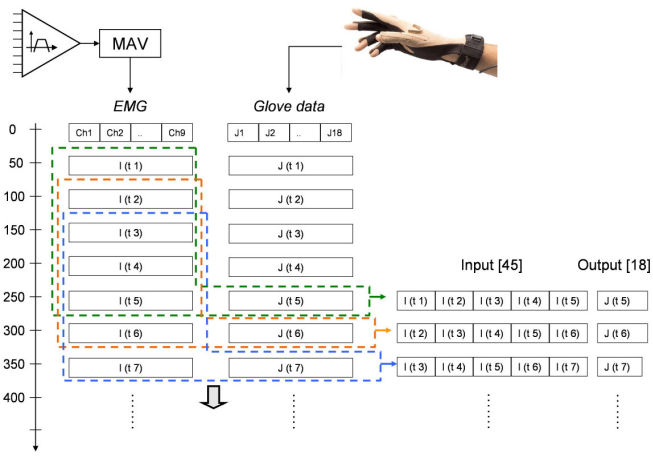

Fig. 2 EMG-glove pattern recognition scheme. I means inputs (nine EMG signals) and J means glove data (18 joints values).

motors of the artificial hand), to resemble the postures of the healthy hand (wearing the glove) with the Cyberhand. In particular, for each finger the metacarpo-phalangeal and proximal inter-phalangeal sensor values from the Cyberglove were linearly combined to obtain the CyberHand flexion position, and the rotation angle from the Cyberglove thumb was directly mapped to the abduction/adduction DoF of the CyberHand. This calibration was performed on an individual basis when donning the glove as it fits each person differently.

The mean of the absolute value (MAV) was the feature selected for real-time classification. A custom made application written in Visual C++ was the core of this classifier; hand control commands were generated and sent to the artificial hand by implementing the following machine learning schema.

1) *Supervised learning phase*: the participant performed synchronous movements with both his hands, and both glove-data (from the healthy hand) and EMGs (from the stump or contralateral arm) were acquired by the PC.

The MAV for each EMG-channel was computed by first rectifying and then smoothing the signal using an exponential band-pass filter [29]. Thereafter the signals were down-sampled with a frequency of 20 Hz by using a moving average filter (500 samples). One extra EMG signal was added containing the computed mean value of the 8 channels. This ninth channel could be used for determining the onset of a movement, and in earlier work it has actually increased the performance of the classifier [11]. Every 50 ms nine new EMG values were available and stored in a push vector memorizing the last five vectors (covering EMG data 250 ms back in time). Accordingly the input data for the classifier was composed of vectors having a dimension of 9 x 5 = 45, i.e. the feature space dimension. The output vector dimension was 18, i.e. all joints data representing the most recent samples of the hand position (cf. Fig. 2). In the supervised learning phase the system learns how to map the EMG patterns to joint-angle outputs.

2) *On-line classification and control*: during this phase, EMG signals were acquired, their MAV were computed, and pattern recognition was performed by means of local

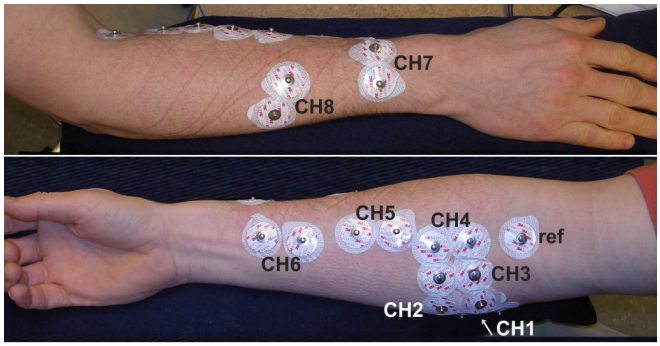

Fig. 3 Location of the eight pairs of bipolar electrodes.

approximation of the input patterns to the training data, using the k-nearest neighbour algorithm (*k*-NN, with *k*=8 and Euclidean distance as the distance metric [32], [33] and lazy learning with linear search method [26]). Briefly, every 50 ms the algorithm searches the data for the eight nearest neighbours of the input pattern; this was done by computing the Euclidian distance (d) between the input pattern and the stored EMG patterns. The d-values are stored on a stack, with the eight best ones on the top of the stack at the end of the search (on our current setup this search takes less than 1 ms). The output is then calculated as their average. This algorithm was used to predict, in real-time, joint positions, i.e., to control the prosthesis postures based on EMG patterns.

New predictions were computed every 50 ms, which was fast enough for the control to be considered as smooth and real-time. This decision stream was post-processed by an exponential smoothing filter (with smoothing factor □=0,15) to eliminate spurious errors in the set-position control commands sent to the hand controller [18]. One of the main advantages employing such control is that learning takes instant effect, as the actual training is merely storage of data making it suitable for real-time control applications [29].

C. *Participant Groups & Experimental Setup*

Ten participants, having given informed consent, took part in the experiments. Five participants - four men (*a1-a4*) and one woman (*a5*) - were transradial amputees (group *a*): demographic data for these participants are presented in Table I. Five other young participants –three men (*b1-b3*) and two women (*b4-b5*), aged 27-32- were able bodied participants with no known history of neuromuscular disorders. The results from an off-line analysis from participant *a2* have been previously documented in [25].

Eight bipolar EMG surface electrodes (Ag/AgCl, from 3M Health Care, Germany) were placed on the participants' right forearms or residual limbs. For both amputees and able-bodied participants, six electrodes (CH1..CH6) were placed on superficial flexor muscles (on the volar-ulnar side of the forearm), and the last two (CH7 and CH8) were placed on superficial extensor muscles as shown in Fig. 3.

The considerable differences between the different stumps in length and diameter influenced the placement of the electrodes: it was therefore impossible to standardize their

localization for amputees. For the participant with the shortest remaining forearm (*a4*), e.g. the electrodes nearly covered the stump. The general purpose of the placement was to achieve recordings from as many different muscles as possible, and the optimization of localization was accomplished by minimizing the cross-talk visually.

TABLE I
DEMOGRAPHIC DATA

ID	AGE	Missing hand	Stump length	Time after amputation	Prosthesis used	Dominant hand
a1	47	Right	24 cm	12 years	Cosmetic	Right
a2	23	Right	16 cm	2 years	Myoelectric	Right
a3	54	Left	10 cm	3 years	Cosmetic	Right
a4	37	Left	9 cm	25 years	Myoelectric	Right
a5	24	Left	11 cm	Congenital failure of formation	Myoelectric	-

The participants were sitting in front of a table with their residual limb lying in a comfortable position, parallel to the artificial hand (cf. Fig. 1). Since only a right artificial hand was available, a mirror was used to create a reflection of the artificial hand on the left side for the three left-hand amputees. A mirror was therefore placed obliquely in front of the participant so that the right-hand prosthesis was reflected and visually superimposed as close as possible to the stump [34].

The goal was to allow the participants to voluntarily perform seven hand movements and prehensile patterns useful for ADLs: A) thumb flexion; B) index finger flexion; C) thumb opposition; D) middle, ring, little finger flexion; E) long fingers flexion; F) tridigital grasp; G) lateral grip/key grip (Fig. 1A-G respectively). Following the pattern recognition scheme previously mentioned, the protocol was divided into two phases: the *supervised learning phase* (where both the participant and the classifier got trained) and the *evaluation control phase* (where the artificial hand was controlled by the participant using EMG in real-time).

In the supervised learning phase each of the seven movements were executed by the participants three times consecutively in response to an auditory cue from the operator, from movement A (the thumb flexion) to movement G (lateral grip). Each trial consisted in contracting and actively holding the contraction for about five seconds (i.e. static contraction) and returning back to a relaxed state for five seconds (no contractions). During this supervised learning phase the system was trained and simultaneously used for controlling the prosthesis, which gave the user immediate feedback of the quality of his control and training. In the evaluation control phase, the same sequence of movements was repeated (three times each, ordered from A to G) for a total of 21 movements, and the EMG pattern was classified into hand postures, which were executed on-line by the CyberHand. This procedure was repeated three times, and after the third evaluation phase the 21 movements were also executed by each participant in a random order.

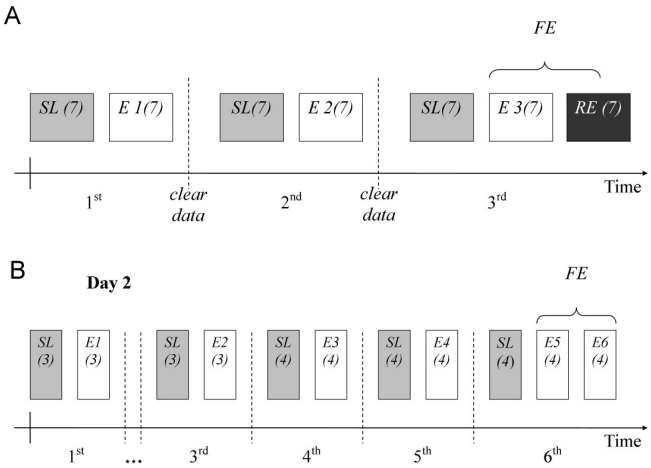

Fig. 4. Experimental protocol (a) One-day experimental session. (b) Second day experimental session for amputee *a5*. *SL* means Supervised learning phase, *E* means Evaluation phase, and *RE* means Random Evaluation phase. Values within parentheses denote the number of hand movements in each session repeated three times each.

Therefore, the final evaluation session (FE in Fig. 4A) consisted of 42 movements. Training data was cleared between each session since participants usually get better at using their muscles with time. A graphical description of the protocol is provided in Fig. 4A.

The woman with a congenital failure of formation (participant *a5*) performed experiments following a different protocol due to her particular situation. Our previous study showed that people with congenital missing limbs have difficulties in generating specific finger movements [31]. Therefore fewer movements were included, but with more repetitions and split in two different sessions, the second session seven days after the first one. Participant *a5* performed five training and evaluation sessions in the first day executing three movements, and six training and evaluation sessions in the second day, with three movements in the first three sessions and four movements in the last four sessions (cf. Fig. 4B). The final evaluation session (on day 2), was twice as long: i.e. four movements, three times each, performed twice (FE in Fig. 4B). This particular protocol has been designed in order to slowly train the participant to perform unused or even "unknown" muscle contractions.

D. Empirical Evaluation

To estimate the real-time classification error, during the evaluation phases, the participant was given five seconds from the time of the cue to generate the corresponding movement (as in [20]). In each evaluation phase, each movement was to be performed three times. For the purpose of system evaluation the 18 joints were subsequently off-line mapped into eight classes (seven movements plus the relax position). Three metrics were used to quantify EMG real-time control performance based on a work by Li et al. [23]. The *motion-selection time* (Ts), defined as the time taken to correctly select a target movement. This quantity represented how quickly EMG command information could be translated into

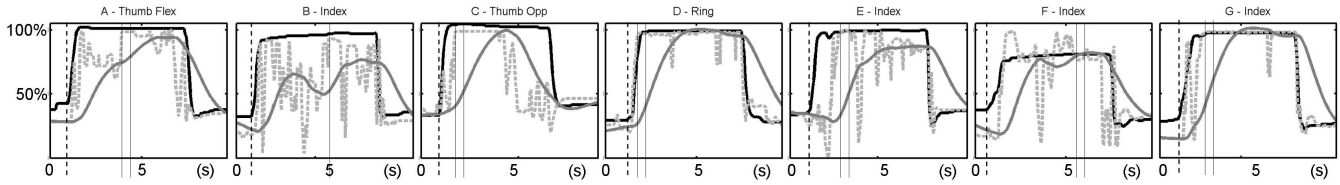

Fig. 5 Outputs of the classifier during one trial for each movement from one evaluation session (participant *a3*). The graphs present: the intended flexion trajectory (bold curve), the classifier output (dashed curve) and the actual measured position from the real hand (grey curve), from significant fingers in the movement (movements and significant fingers plotted defined in top of the graphs). Vertical lines denote the movement onset (dashed), the motion-selection and motion-completion times (thin lines).

the correct motion predictions. It was measured as the time from the onset of movement to the first correct prediction of the movement. The onset of movement was identified as the time of the last *no movement* (relax) classification; this corresponded to approximately a 5% increase in the computed mean absolute value (ninth EMG channel) of the baseline EMG signals. The *motion-completion time* (Tc), was the time corresponding to ten consecutive correct classifications as a new classification occurs every 50 ms. The *motion-completion rate* (MR in the graphs), or *classification accuracy* was defined as the percentage of successfully completed motions. This metric was a measure of performance reliability [23]. The motion-selection and motion-completion time of a movement was counted only if the movement was successfully completed within 5 s.

Statistical differences among experimental motion-completion rates were evaluated using the Friedman test. Differences in time metrics were evaluated using the two-sample Kolmogorov-Smirnov test. If the Friedman test suggested that there was a difference, groups were compared pair wise using the Bonferroni adjustment. A level of $p < 0.05$ was selected as the threshold for statistical significance. The statistical analysis was performed using MatLab (The MathWorks, Natick, MA, USA) scripts.

I. Results

The results are based on the processing of EMG data recorded from 8 electrodes, from 5 amputees and 5 able-bodied participants, in four evaluation sessions. In the performed experiments, the mean classifier dimension, i.e. the mean number of vectors used for supervised learning, was 3887 (equivalent to 194 sec training duration). This means that the system produced outputs for controlling the hand, searching and averaging among 3887 possible postures. This section firstly presents results for the traumatic amputees (*a1*..*a4*) and able-bodied participants; thereafter the results achieved by participant *a5*, for whom the experimental protocol was significantly different from the others.

Fig. 5 shows the outputs of the EMG classifier during some significant trials from participant *a3* (worst performer) executing all movements, isolating one repetition for each movement. The graphs show three output curves related to one single finger representative for the movement (e.g. the thumb flexion for movement A, the index for movement B, etc.). The bold black curve represents the intended movement (as taken to successfully complete a movement through the full range of motion. It was measured as the time from the onset of movement to the completion of the intended movement, calculated as in [23] as the time of the tenth correct classification. Ten accumulated correct classifications were required for a motion completion. The minimum possible time to complete any motion was normalized to 0.5 s, recorded from the data-glove), the dashed curve is the classifier output, and the light grey curve is the prosthetic hand real-time posture (i.e. what the participant was actually seeing) that takes into account of the mechanical response delays of the system. The dashed vertical lines represent the beginning of the movement and the thin vertical lines indicate motion-selection and motion-completion times respectively (if present). From the comparison of the curves it is possible to understand the differences between the output of the classifier, and the actual trajectory performed by the fingers (as recorded from the encoders). Rapid changes in the output of the classifier are not followed by the hand, that responds as a low pass filter (with a mechanical pole approximately at 0,4 Hz). In addition it is possible to recognize when the movement is classified (dashed and bold curves overlapped), and when a movement was physically performed (when the light grey curve overlaps the others). In particular, only movement D was clearly executed from the beginning; other movements were classified after an initial error (A, C, G) and other were significantly unstable (B, E, F).

Table II shows the evolution of classification accuracy, Ts, and Tc during the evaluation sessions (E 1, E 2, and FE divided in the graphs into E 3 and RE, cf. Fig. 4). Globally accuracies improve with time both for traumatic amputees and for able-bodied participants, but with no statistical significance. Time metrics show different trends with no statistical differences between trials. The four graphs in Fig. 6 show motion-completion rates of each traumatic amputee, on each class of movement varied across sessions (therefore across training sets); figures are based on six trials for each movement. Participants *a2* (91%, 81%, 98% across E 1, E2 and FE) and *a4* (91%, 86%, 86%) obtained higher accuracies compared to *a1* (57%, 67%, 69%) and *a3* (48%, 52%, 62%).

The graph in Fig. 7 represents individual performance metrics for the participants in this study, in the final evaluation phase, performing the seven movements. *Light grey* bars represent the classification accuracy for each participant (values to be read on the left Y axis), *white lozenges* denote Ts

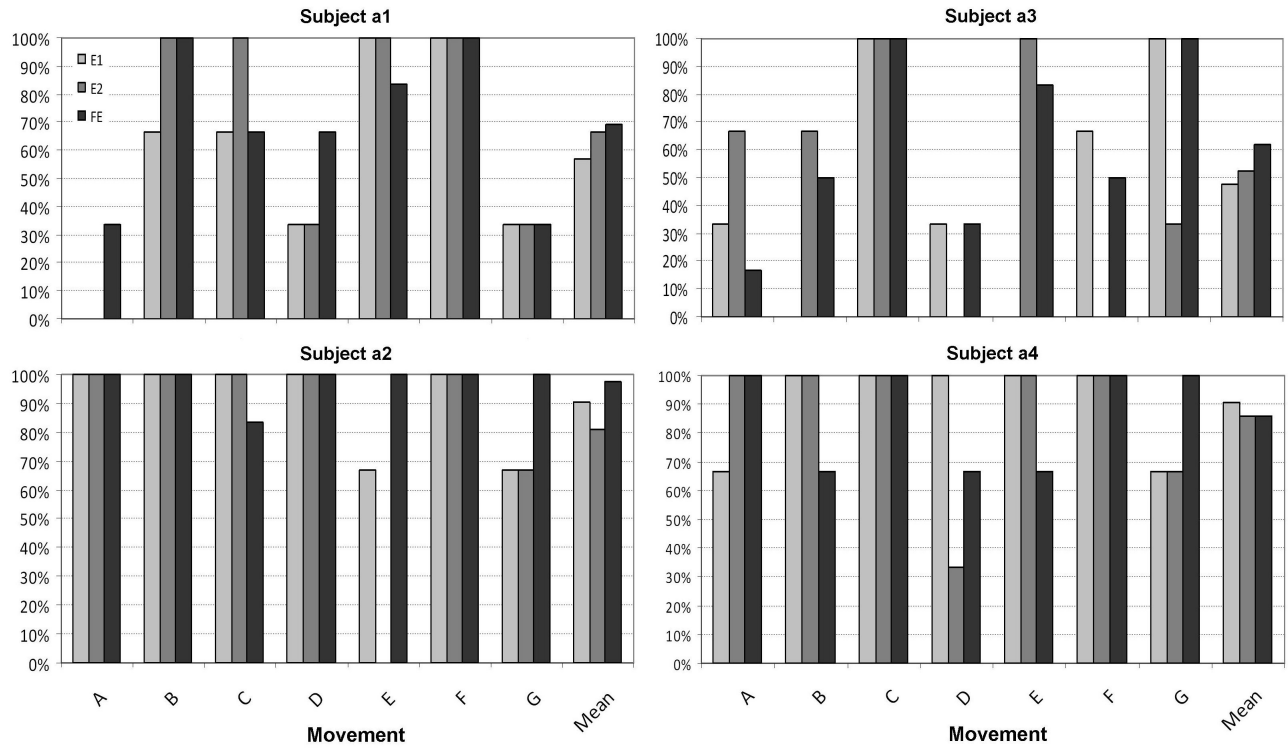

Fig. 6 Motion-completion rates of each amputee, on each class of movement varied across sessions.

and *black lozenges* Tc (right Y axis). It is interesting to note that the accuracy for the best amputee (*a2*) is equal to that of the best able-bodied participant (*b5*), and very good (98%). Participant *a2* selected and completed movements much faster than *b5* (Ts 0.2 s vs. 1.14 s; Tc 0.8 vs. 1.83 s), therefore *a2* globally performed better than *b5*. Among the amputees, the lowest performance was achieved by participant *a3*, with only 62% of successful movements. It is important to point out that this participant suffered from phantom limb pain that imposed us to interrupt the experiments several times in order for the participant to rest. Moreover, being a cosmetic hand user he was not used to contract his forearm muscles.

Fig. 8 summarizes and compares the averaged classification accuracies achieved by the two groups based on the seven movements. The data includes all participants, in their final session (*FE* in Fig. 4), i.e. when performance is presumed to be highest. The light grey bars of the graph refer to the group of traumatic amputees, the dark grey to the able-bodied participants (group *b*). White markers (lozenges and triangles) indicate Ts, whereas dark grey ones denote Tc. Group *b* globally performed better than amputees (89% vs. 79%). Movements D, F and G were performed with considerably higher accuracy by group *b*. The best accuracy was obtained by group *b* performing movement D (middle, ring and little flexion), correctly classified 30 times out of 30. Time metrics vary among the movements: some of them were performed faster by group *b* (movement A, D), some by the amputees (B, E, G), and a few (C, F) similarly; globally amputees achieved better results in terms of time metrics compared to group *b* (see also Table II). The classification accuracy of the real-time classifier, discriminating seven movements and considering the nine participants was about 84% in accordance to previous similar research [11], [16], [21], [23], [24].

TABLE II
PERFORMANCE METRICS VS. TIME/EVALUATION TRIAL

	Traumatic amputees				Group *b*			
	E 1	E 2	E 3	RE	E 1	E 2	E 3	RE
MR (%)	70	73	80	77	86	88	91	88
			79				89	
Ts (s)	0.85	0.70	0.55	0.77	0.73	0.65	0.78	0.79
			0.67				0.78	
Tc (s)	1.55	1.37	1.25	1.36	1.36	1.32	1.37	1.42
			1.30				1.40	

A Friedman's test on the classification accuracies reveals several interesting points, in agreement with expected outcomes and highlighting interesting issues. There is no statistical difference in accuracy among able-bodied participants ($p = 0.3628$), whereas amputees' results are significantly different ($p < 0.001$). This means in other words that able-bodied participants belong to the same group (as actually expected), while amputees do not, which is reasonable considering the differences in stumps, age, etc., described in Table I. The hypothesis is that amputees are divided in two groups: myoelectric hand users (hereafter *aM*) and cosmetic hand users (*aC*). The former are trained and used to contract their muscles to operate their artificial limb, while the latter are not (or at least less). The hypothesis, which is visually

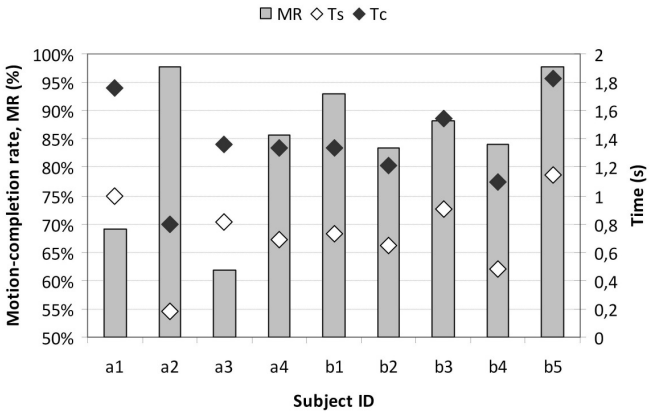

Fig. 7 Comparison between participants and groups in the final evaluation session. Left Y axis: mean classification accuracy in light grey bars; each column is based on 3x7x2 movements. Right Y axis: mean motion-selection time, Ts (white lozenges) and motion-completion time, Tc (black lozenges).

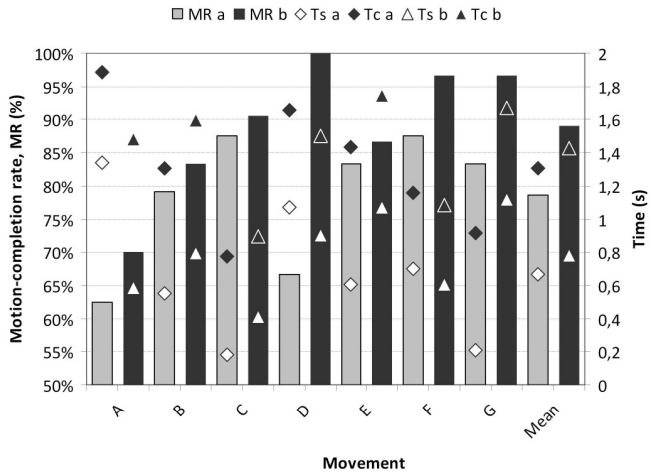

Fig. 8 Comparison between movements (corresponding to letters as defined) and groups in the final evaluation session (figures are calculated based on 5 x 6 trials for group *b* and on 4 x 6 trials for amputees). Left Y axis: grey bars present motion-completion rate, for traumatic amputees and able-bodied participants based on all movements. Right Y axis: mean motion-selection time, Ts (white markers) and motion-completion time, Tc (dark grey markers) for amputees (lozenges) and able-bodied participants (triangles).

supported by the graph in Fig. 7, is also confirmed by the Bonferroni test: participants *a1* and *a3* (*aC* group) belong to the same distribution (p = 0.4913), and the same occurs for *a2* and *a4,* the *aM* group (p = 0.0588). The comparison between *aC* and *aM* gives a p value equal to $3.2 \cdot 10^{-5}$ meaning that the groups are statistically different. Participant *a5* was deliberately left out of this analysis since she is a congenital amputee, therefore different from the other cases. The second hypothesis is that myo-prosthesis users and unimpaired participants belong to the same group. Again the Friedman test confirmed this statement: comparing group *b* and *aC* yields a p-value equal to 0.0337 (significantly different), and comparing group *b* and *aM* gives a p-value of 0.88 (statistically equal).

The frequency of occurrence graphs in Fig. 9 present the percentage distribution of the time required for the successful selection and completion of all attempted movements during the final evaluation session (percentages are referred to the number of correctly executed movements for each group: 132 movements for amputees and 189 for able-bodied participants). The graphs show similar trends, and the majority (over 80%) of successfully achieved movements are selected within 1.25 s and 1.35 s for amputees and able-bodied participants, and completed within 2.25 s. These differences were not statistically significant (p = 0.26 for Ts and p = 0.74 for Tc). Statistical differences in motion-selection times distributions are not found within able-bodied participants (p = 0.644) and not even within traumatic amputees (p = 0.058). Though, in the latter case, the p value is close to the significant figure; therefore, comparing amputees pair wise statistically differences are found between *a2* and *a1* (p = 0.025) and *a2* and *a4* (p = 0.014) (between *a2* and *a3* p is 0.059). Same figures are found for the motion-completion times.

Results from participant *a5* are presented hereafter. Table III shows how performance metrics varied across sessions and days for the congenital amputee. The trend for accuracy is clearly positive, reaching a 100% success at the end of both days, whereas time metrics are highly variable.

Graphs in Fig. 10 show the performance metrics in the final evaluation phase (comprising E6 and RE) based on 24 movements in total: participant *a5* successfully completed 23 movement out of 24, 80% of which within 1 second. Finally, motion-completion rate from participant *a5* is statistically compared with the different representative groups (*b*, *aC* and *aM*) only considering the four movements performed (B, D, F, G), resulting in non-statistical differences (p > 0.8 against *aM* and *b,* p > 0.1 compared to *aC*).

I. Discussion

This paper confirms previous studies demonstrating that it is possible to decode hand gestures in *real-time* using EMG-patterns in transradial amputees and to *intuitively* control an artificial hand with great *accuracy*. Furthermore, we show that using the presented classifier there is no difference in decoding accuracy between unimpaired participants and myoelectric hand users, whereas there is a difference between unimpaired participants and cosmetic prostheses users, in absence of training. It is worth saying that all the statistical analysis here presented should be supported by further work on a larger group. One surprising outcome is that the congenital amputee managed to control four movements to a high degree of accuracy.

A. On the Proposed Architecture

The presented system represents an effort - using non-invasive techniques - to narrow the gap in current control technology for individuals with a hand amputation at a transradial level. For these individuals, with most of the forearm sensory-motor system still intact, a TMR procedure [4] would probably be too invasive and therefore its employment debatable. TMR is clearly more suitable for proximal amputations, where the original musculature for

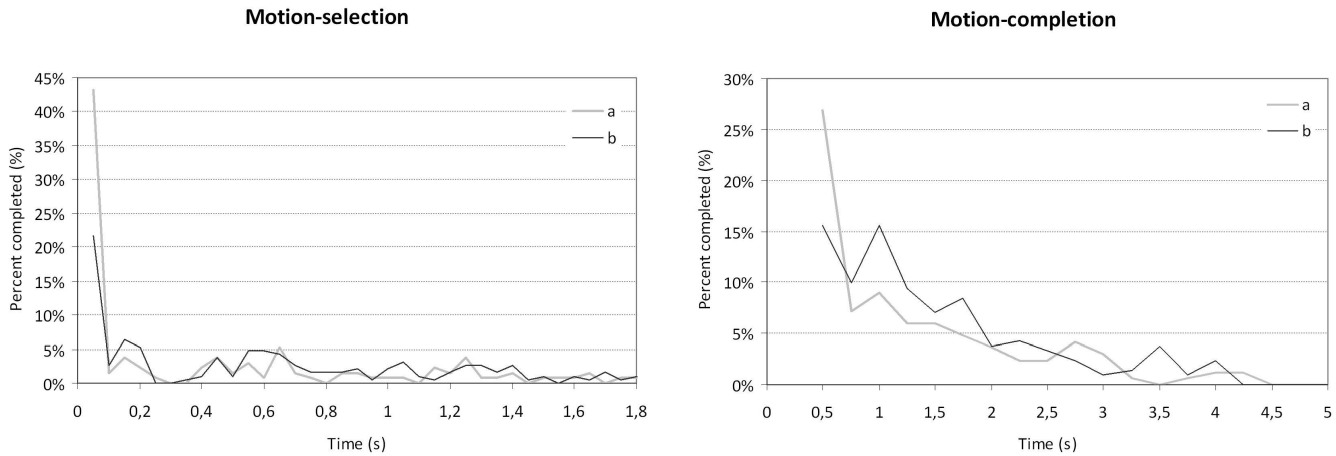

Fig. 9 Frequency of occurrence for motion-selection time (left panel) and motion-completion time (right panel) for amputees (light grey curves) and able-bodied participants (dark grey curves) during the FE session. The Y axes represent the percentage of attempted movements selected or completed within time bins of 0.05 s and 0.25 s, respectively. The motion-selection time graph presents 92% and 91% of samples from amputees and able-bodied participants, respectively.

controlling the hand is no longer accessible. Consequently, transradial amputees could benefit from either peripheral neural implants [5] or from an advanced non-invasive interface such as the one here proposed, for an increased and more natural control of next-generation robotic prostheses.

The main advantage of this controller, with relation to the three key issues previously mentioned is related to its intuitiveness. Finger movements of the artificial hand are controlled by exactly executing the original physiological movements unlike most of the pattern recognition systems developed earlier, where different hand functions (or grasps) are usually remapped to wrist movements [16], [18]-[20], [22]. Moreover the control is continuous: i.e. the signal modulation can move from one movement to another without first going to the relax (rest) posture. This is desirable from the user's point of view as it is more efficient and results in a seamless function transition [1].

The k-nearest neighbors decision rule is the basis of a well-established, high performance pattern recognition technique [32], [33]. It is a typical example of instance based (memory based) learning, i.e. that it constructs hypotheses directly from the training instances themselves [32]. Thus, as soon as the training data is recorded the system is ready for real-time control. This causes two main drawbacks: the longer the training is (i) the larger memory space is required and (ii) the pattern recognition algorithm requires more time and computing to search through the entire learning data set to find the nearest neighbour and produce an output. In the present architecture, using a standard desktop PC (Intel Pentium M, clock speed 2.1 GHz, and 2 GB RAM), none of such drawbacks affected the experimental outcomes: every 50 ms a new output was correctly produced (but less than 1 ms was required for each search) and the mean memory space required in the sessions (for a 194 seconds mean training duration) was about 840 kbytes.

The entire delay of the system accounts for the classifier delay (50 ms) and for the internal controller delay of the hand (< 5 ms); therefore this control system is reactive enough to be considered as smooth and real-time.

Finally, as mentioned in [16], there is no practical limit to the number of electrodes that can be integrated into a prosthetic socket, therefore, the number of electrodes used in these experiments should not be considered a hindrance toward embedding in an actual prosthesis.

A. *On the Experimental Outcomes*

Graphs in Fig. 6 show that cosmetic hand users (*a1* and *a3*) globally increased their performance over time. Even if this effect is not supported by statistics, it seems natural when considering that they had not used their muscles for a long time and therefore some training was needed before being able to generate significant and coherent muscle contractions. However, there is an extra consideration to take when working with cosmetic hand users: it is possible that the stump might not have developed protection around the tendons that have been reattached to the remaining bone structure, which will produce an increased irritation of the stump. Therefore for a short term comparison, the current protocol would be suitable, but for longer term applications, a period of adaptation is required to really appreciate the performance of the system on cosmetic hand users. Conversely, in myoelectric hand users (*a2* and *a4*) this trend is not evident: since they performed well from the beginning there is no statistically significant improvement in subsequent sessions. The explanation is that since they have a well trained motor system, the EMG signals had high correlation with the recorded movements, from the beginning of the experiments. The importance of the training level is also confirmed by the Friedman test: cosmetic hand users motion-completion rates were statistically different from unimpaired participants and myoelectric hand users, whereas these last two groups belong to the same distribution. This result also reveals that further developments of the present classifier could be assessed with just able-bodied participants.

In agreement with [23] there was no difference in time metrics between the amputees and unimpaired subjects. Movements were successfully performed in 5 s or less by

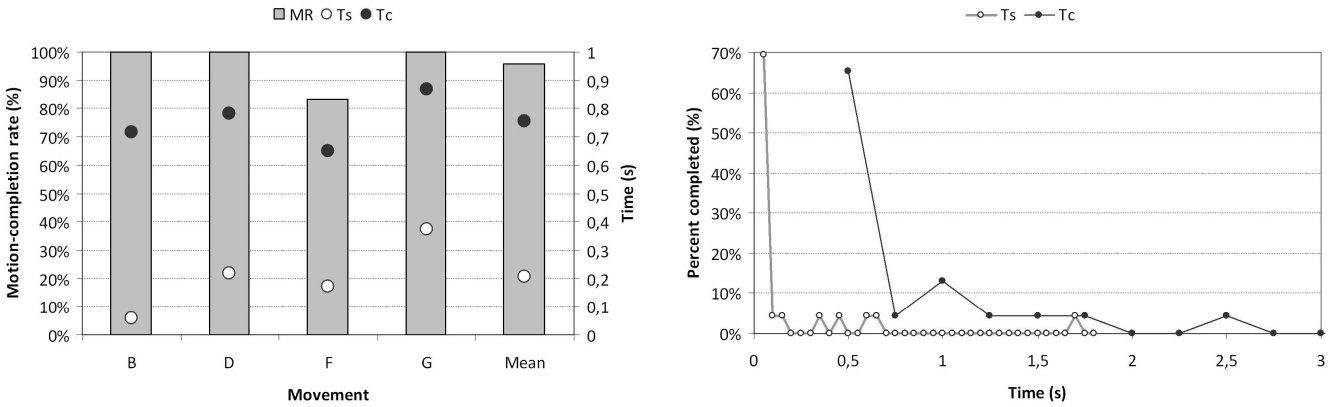

Fig. 10 Metrics for the congenital amputee during the final evaluation session. Left panel: motion-completion rate (grey bars, left Y axis); motion-selection (white circles) and motion-completion (black circles) times (right Y axis). Right panel: frequency of occurrence for motion-selection time (white circles) and motion-completion time (black circles); the Y axis represents the percentage of attempted movements selected or completed within time bins of 0.05 s and 0.25 s, respectively.

TABLE III
CONGENITAL AMPUTEE PERFORMANCE METRICS VS. TIME/EVALUATION TRIAL

	Day 1					Day 2						
	E1	E2	E3	E4	E5	E1	E2	E3	E4*	E5*	E6*	RE*
MR (%)	88	83	90	89	100	40	60	70	92	92	92	100
Ts (ms)	120	160	190	450	50	660	210	220	170	1070	60	35
Tc (ms)	570	645	740	900	500	1110	1060	985	865	1705	560	935

Percentages are based on three movements repeated three times; the last four sessions of day 2 (denoted by asterisks).

amputees as quickly as by able-bodied participants (but fewer movements were successfully performed by amputees). Considering time metrics, the only statistical difference is for participant *a2*, being faster than other amputees (and able-bodied participants, cf. Fig. 7) in performing and completing the movements. Explanations for the better performance of subject *a2*, may be related to his age, short time after amputation (cf. Table I) and to the exceptional qualities of the participant himself (he practices sports, plays the drum, carrying out a "normal" lifestyle). This may have cognitively trained him to use forearm muscles in a very conscious way compared to other less-active amputees and unimpaired people.

The subject with a congenital failure of formation is of special interest. She had a simpler training protocol beginning with three movements and in the last day increasing to four. The participant was a well-trained myoelectric hand user and thus had earlier used muscles, but just for opening and closing one grip. Surprisingly she managed to control all four movements to a very high degree of accuracy (96%, cf. Fig. 10) and short completion times (80% within 1 s). This is an interesting outcome as it indicates that the motor system of the amputee is still highly organized and little effort was needed to mobilize the right areas of the motor brain cortex to induce these movements. It is known that patients with congenital failure of formation can induce imaginary movements in their missing hands and that such procedures are associated with activity in the motor cortex [35]. One possibility is that sleeping motor areas, present since birth, are awakened and brought into action. Another explanation is that adjacent cortical areas are recruited into new functions induced by training.

A. *On the Experimental Setup*

EMG electrodes are typically placed on the muscle belly of the targeted muscles; this however would demand more electrodes as there are 19 muscle groups in the forearm, not perfectly separated in both unimpaired and amputees (especially for very short stumps). Moreover since the important issue for this classifier is to recognize unique EMG patterns from the electrode matrix, the optimal placement is not necessarily on the top of muscle bellies. However, performances would possibly increase by individual adjustment of electrode positioning, optimizing amplification and noise levels, and optimizing filter parameters to the EMG responses.

As in all previous research related to dexterous prosthesis control using pattern recognition techniques, the experiments here presented have been done in a very well controlled environment, with the stump (or forearm) of the participants in a comfortable position. This study represent a preliminary step towards the development of a naturally controllable hand using non-invasive interfaces, and to achieve this goal the future version of the controller must be able to deal with muscular activity of a free-to-move residual limb.

The data-glove was employed to associate in a simple manner, continuous EMG activity to continuous hand postures, and for determining off-line the onset of the movement. In another setup, the glove could be removed and visual input cues be used. This would be useful for bilateral amputees.

The movements selected for the experiments have been chosen purposely to fit the possible movements of a prosthetic hand being under development, having an independently

actuated thumb flexion, thumb abduction, index flexion, and the last three fingers (middle-ring-little) mechanically coupled [36].

B. On the Suitability for Actual Dexterous Prostheses

The control architecture presented in this paper has been used to demonstrate the feasibility of controlling finger movements with great accuracy. It is currently not suitable for integration into a real prosthetic socket to be used by transradial amputees, as it employs non-portable components for acquiring and processing EMGs: bulky laboratory amplifiers and a traditional desktop computer with a data-acquisition card.

The data acquisition circuit could be miniaturized employing surface mount operational amplifiers and multiplexing the buffered and high-pass filtered EMG channels at the cost of a sampling rate reduction. The pattern recognition could be implemented using a state of the art embedded architecture with a microprocessor and a real-time operative system or a FPGA. It should be noted here, that very fast processors and DSPs are nowadays available (TI C6000 series clocks at up to 1,2 GHz, Freescale MSC8154 up to 1 GHz, Analog Devices Blackfin up to 600 MHz). Doing only "data-crunching" on the embedded processor (no graphics) should enable a slower processor to do this. The memory requirement (that strongly affects size and power consumption of the embedded circuits) is not critical as well; considering a 180 seconds training (as in the present experiments), and using memory compression techniques, about 256 kBytes (2 Mbit memory, commercially available) would be needed, without changing the pattern recognition architecture. Finally this system could be used in combination with transradial prostheses with independently actuated fingers like the i-LIMB (Touch EMAS, Ltd., Scotland) or with recent advanced research devices [2].

Combining these suggested systems would bring about an architecture well suited for functional testing of the whole system on transradial amputees. Future investigations will include the interaction with objects (real grasps) and the development of a pattern recognition system adaptive to the different possible stump positions, allowing the accomplishment of activities of daily living.

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