Characterization of EMG Patterns From Proximal Arm Muscles During Object- and Orientation-Specific Grasps

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***Abstract*—Reach-to-grasp tasks are composed of several actions that are more and more considered as simultaneously controlled by the central nervous system in a feedforward manner (at least for well-known activities). If this hypothesis is correct, during prehension tasks, the activity of proximal muscles (and not only of the distal ones used to control finger movements) is modulated according to the kind of object to be grasped and its position. This means that different objects could be identified by processing the electromyographic (EMG) signals recorded from proximal muscles. In this paper, specific experiments have been carried out to support this hypothesis in able-bodied subjects. The results achieved seem to confirm this possibility by showing that the activation of proximal muscles can be statistically different for different grip types. This finding supports the hypothesis that proximal and distal muscles are simultaneously controlled during reaching and grasping. Moreover, this kind of information could allow the development of an EMG-based control strategy based on the natural muscular activities selected by the central nervous system.**

***Index Terms*—Biorobotics, electromyographic (EMG) signals, hand prosthesis, reach-to-grasp, upper arm.**

I. Introduction

PREHENSION movements are achieved through the combination of different actions such as transport, manipulation, and—as recently shown—hand orientation [1]. For many years, starting from the visuomotor channel hypothesis [2], [3], the movements related to the different actions have been considered as independently controlled by the central nervous system (CNS). In the recent past, evidence has been provided about a possible coupling of the different actions. For example, humeral rotation is strictly related to object orientation [4], and transport time and peak velocity can be simultaneously affected by object size [5]. In general, a significant relationship between arm transport and hand orientation seems to exist in reach-to-grasp tasks [6].

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This has also been confirmed by Lemon and coworkers [7] who showed that specific upper limb electromyographic (EMG) activities can be identified in monkeys while grasping different objects. In this case, the intrinsic muscles and the long flexor muscles seem to be involved only during the phase related to the production of force while all the other upper and lower limb muscles were active during all the different phases showing a significant interdependence among the actions carried out during the reach-to-grasp.

Moreover, a feedforward control strategy seems to be implemented by the CNS to carry out prehension movements, as shown in [1] and [8]. In particular, Fan and colleagues showed that, even if feedback control is useful to smooth trajectories, the feedforward model plays a very important role in the definition of the motor control strategies.

These results show the strong relationship existing among the different components of reach-to-grasp tasks and the preference of a feedforward model. Thus, this object-dependent modulation of EMG activity could also be found in proximal muscles in human able-bodied subjects. This could allow us to discriminate different grasping tasks without the need to record activities from more distal muscles (e.g., intrinsic ones). The validation of this hypothesis could be very useful toward a better understanding of the mechanisms of movement control for reaching and grasping. The degree of task-specificity of the arm muscles for the grasp of different objects is of paramount importance to this aim.

This analysis could also be useful to develop an EMG-based algorithm to control robotic systems. In fact, EMG signals have been used in the last decades for the development and control of different robotic platforms: artificial prostheses [9]–[16], exoskeletons [17], [18], and teleoperated devices [19]–[21].

In this paper, experiments have been carried out in order to support the hypothesis that this "upper arm muscle modulation hypothesis" is valid. In particular, EMG signals from several proximal muscles have been recorded in able-bodied subjects while grasping different objects placed in the different positions and they have been used to test this hypothesis.

II. Methods

A. Subjects

Six able-bodied subjects (three males, three females, mean age 31.67 years, SD 6.02, three right-handed and three left-handed) provided their consent to participate in this study after being informed about the experimental procedures. In Table I, the anthropometric data of all the participants are given.

TABLE I
ANTHROPOMETRIC INFORMATION RELATED TO DIFFERENT SUBJECTS INVOLVED IN EXPERIMENTS

Subject	Age (yrs)	Sex	Dominant Limb	Height (cm)	Weight (Kg)	Limb size (cm)
1	32	Male	Right	172	61	73
2	37	Male	Left	175	75	75
3	38	Male	Right	170	62	70
4	34	Female	Left	156	59	62
5	23	Female	Right	156	44	60
6	26	Female	Left	160	48	68

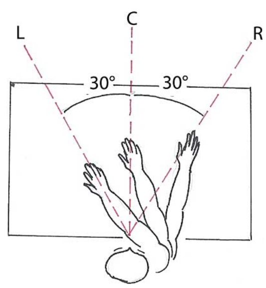

Fig. 1. Experimental setup: the subjects were asked to reach and grasp different objects placed in three different positions (L, C, and R).

All subjects were healthy with no known history of neurological abnormalities or musculoskeletal disorders.

B. Experimental Procedure

Subjects sat comfortably in front of a table and they were asked to move, starting from an assigned position, the dominant arm toward an end position, and then to grasp an object (see Fig. 1). Each subject had to grasp and hold for 2 s, three different objects (a can (C), a tennis ball (B), and a key (K) that could turn into a lock fixed over the top of a cylinder) placed in three different table positions. The different sizes of the objects have been selected in order to allow different grip types [22]: the can is grabbed with a palmar grasp, the tennis ball with a spherical grasp, and the key with a lateral grasp. The movement started from a position of the hand, flat on the table, in the midline of the body at a distance of about 8 cm from the chest. The objects were placed in order to allow the subjects to perform the maximal elbow extension in three directions (position $L = 30^\circ$ in the contralateral hemisphere, position $C = 0^\circ$, position $R = 30^\circ$ in the lateral hemisphere) (see Fig. 1).

A free view of the arm was allowed during experiments and no instructions that stressed time or accuracy constraints were given. The height of the chair was regulated so that the elbow was supported on the table with an angle of 90° (maintaining the trunk erected). Each subject grasped, at a free arm speed, each object five times for the three positions (in total, 45 grasping trials) with a rest period of 10 s. The order of the grasping trials was random in order to exclude learning phenomena. Subjects were requested not to bend and rotate the trunk, and to prevent translational motions at the shoulder. During the experiments, subjects were restrained in order to minimize thoracic movements, using a commercial system commonly used to secure quadriplegic subjects in the wheelchair and keeping the contact with adjustable armrest (for the nondominant arm) and backrest. Moreover, particular attention was devoted to verify the correct posture of the subjects during sitting before starting the experiments.

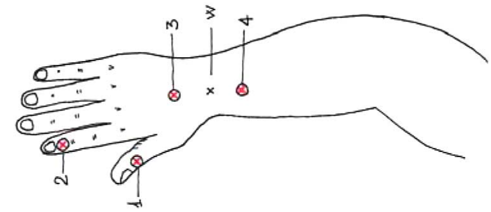

Fig. 2. Position of the markers of the Fastrak system.

C. Apparatus

Movement kinematics (arm positions and movements) were monitored through a Fastrak system (Polhemus, Colchester, VT, USA). This system, used in a number of studies that have investigated upper limb movement biomechanics [23]–[26], is based on an electromagnetic field to determine 3-D positions and orientations of markers relative to the stationary system. Four spatial tracking system markers operating at a frequency of 30 Hz were used. They were positioned, on the dominant arm, over the thumb, the index, and near the wrist (the first point around 5 cm from the center of the wrist toward the middle finger; the second point around 5 cm from the center of the wrist toward the center of the elbow, see Fig. 2).

The Noraxon TeleMyo 2400R (Noraxon, Scottsdale, AZ, USA) was used to collect raw surface EMG data through a wireless unit (TeleMyo 2400T). Raw data were then acquired at a frequency of 1.5 kHz, 1st order 10 Hz hardware high-pass filter, 8th order 500 Hz hardware Butterwoth low-pass antialiases filters, resolution of 12 bits, hardware gains of 1000, and stored for an offline analysis in MATLAB (The MathWorks, Natick, MA) environment. One of the eight TeleMyo 2400T channels was used for the synchronization of the data coming from the Fastrack, whereas other six channels were used to record EMG activities from the trapezius pars ascendens, deltoideus pars anterior, biceps brachii caput longum, triceps brachii caput longum, flexor carpi radialis, and extensor carpi radialis. Disposable 20 mm prejelled Ag–AgCl surface electrodes (Arbo electrodes, Tyco Healthcare, U.K.) in bipolar configuration with an interelectrode distance of 10 mm were used for EMG recording. After the skin surface was cleansed with alcohol, the electrodes were located for optimal signal detection based on [27] and [28].

D. Data Analysis

Raw EMG signals have been filtered with an analog low-pass second-order Butterworth filter with a cutoff frequency of 500 Hz. The resulting signals have been filtered with a high-pass 8th order forward–backward Chebyshev filter with the stopband ripple being 20 db down and a stopband edge frequency of 20 Hz (for suppression of the motion-related artifact). To construct a linear envelope, full-wave rectification was performed, followed by smoothing with a low-pass second forward–backward Butterworth filter (cutoff frequency 10 Hz).

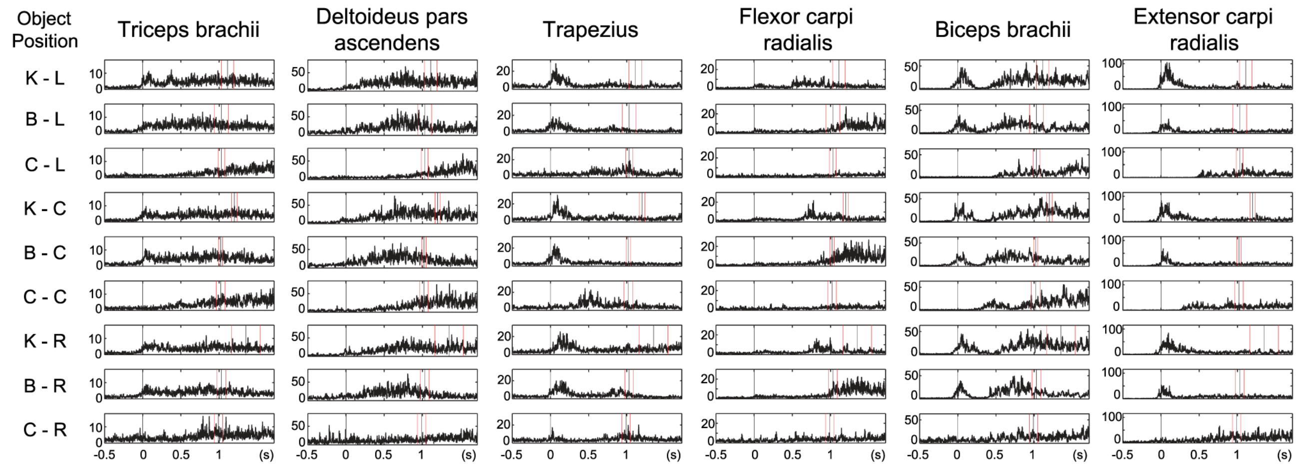

Fig. 3. Rectified and averaged EMG activity during grasp of different objects placed in different positions (L, C, and R). Black vertical lines indicate the onset and the offset of the reaching phase. Red vertical lines indicate the standard deviation of the offset times. Objects: C = can, B = tennis ball, and K = key.

Movement onset (starting of the reaching phase) and offset (contact with the object and end of the reaching phase) have been calculated from Fastrack data. In particular, onsets and offsets have been considered as the times when the wrist linear velocity exceeded or fell below the 5% of the corresponding peak maximal velocity [29]. The whole movement time, corresponding to the reaching phase, has been normalized (onset time = 0% and offset time = 100%).

The amplitude of EMG signals, between the detected onset and offset instants of movement, was converted into three different activation levels (white no activation, light gray from 0% to 33%, gray from 33% to 66%, and black from 66% to 100% of the difference between the peak of the rectified signal and the threshold that represents the rest activity) [30].

Even if sophisticated and interesting algorithms have been proposed in the literature to solve the problem of onset detection of EMG activity [31], a basic but computationally efficient approach that involves the identification of the point where the mean of a selected number of samples exceeds a threshold (rest activity) by a specified number of standard deviations [32] is commonly used. In this paper, for estimating the time instants of muscle contraction, an algorithm based on [11] and [33] has been applied to the EMG signals. The use of a generalized likelihood ratio (GLR) test increases the accuracy of detection even for low levels of EMG activity.

To take into account the temporal information and the nonstationarity of EMG signals, they were analyzed during four different incremental time spans (corresponding to 0%–25%, 0%–50%, 0%–75%, and 0%–100% of the reaching phase) and four different sliding time spans (corresponding to 0%–25%, 25%–50%, 50%–75%, and 75%–100% of the reaching phase).

In order to investigate the object-specific activation of muscles during grasping, an index of similarity [7], [34] has been used. For each time span, EMG activity was averaged, normalized, and then each object was represented by an n-dimensional muscle vector (NDMV). Each dimension corresponds to the averaged and normalized activity for a given muscle. The degree of similarity between these NDMVs was ascertained by computing the Euclidean distance (D) between a pair of NDMVs (NDMV_i and NDMV_j) [highest values refer to lowest level of similarity and vice versa, see (1)]

$$D_{ij}^2 = \sum_{k=1}^{N} (\mathrm{NDMV}_{ik} - \mathrm{NDMV}_{jk})^2. \qquad (1)$$

E. Statistical Analysis

A three-way analysis of variance (ANOVA) was performed to analyze the effects of muscles, positions, and objects on activation levels of averaged EMG signals during reaching. The ANOVA test was followed by a post hoc Bonferroni test. The significant level was selected at 0.05. The processing of kinematics, EMG data, and the statistical analysis were performed using MATLAB (The MathWorks, Inc, Natick, MA) software.

III. Results

The results presented are based on the processing of EMG data recorded from six muscles during five sessions. In each session, subjects were instructed to reach and grasp one of the three objects (can, tennis ball, and key) placed in one of the three different table positions (L, C, and R). Data were rectified and averaged across all the trials for each object and position using the onset of the movement as a reference event.

In Fig. 3, typical averaged EMG signals are given for all the six muscles and every position and object. The black vertical line on the left represents the onset of the reach-to-grasp movement. The black vertical line on the right represents the contact with the object to be grasped and its standard deviation (red lines). All these events have been calculated from the kinematic data recorded with Fastrack. The mean reaching time range from 1.12 ± 0.24 s to 1.288 ± 0.36 s.

The duration of the movements and of the EMG patterns can differ in accordance with the different movements and objects (see Fig. 3). The pattern of activation of some proximal and distal muscles (e.g., trapezius, biceps, and extensor carpi radialis) was similar for the reach-to-grasp of the key and of the tennis ball, independently from the position of the objects, but differences

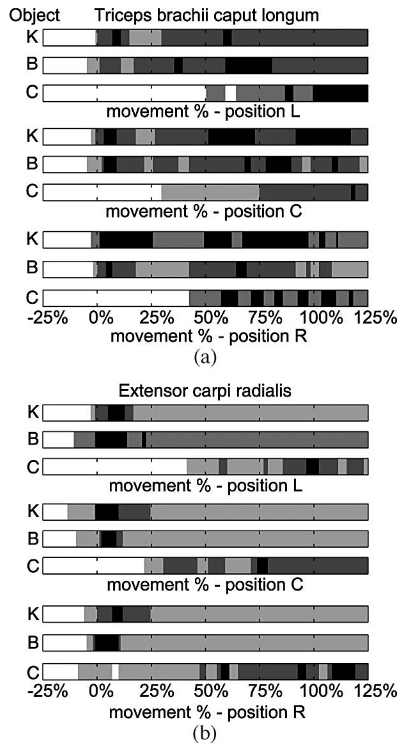

Fig. 4. Levels of activation for the triceps brachii caput longum (top panel) and for the extensor carpi radialis (bottom panel) for one left-handed subject during the different grasping tasks. EMG signals were converted into four different activation levels (white no activation, light gray from 0% to 33%, gray from 33% to 66%, and black from 66% to 100% of the difference between the peak of the rectified signal). Onset and offset time intervals have been calculated as percentage (%) with respect to the whole reaching time (100%). Positions: L, C, and R; Objects: C = can, B = tennis ball, and K = key.

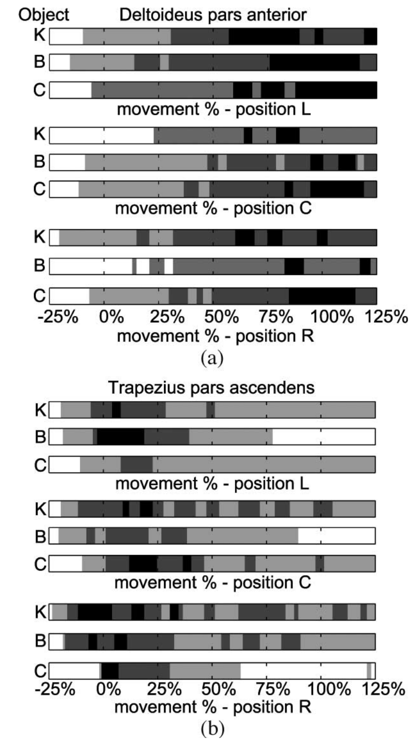

Fig. 5. Levels of activation for the deltoideus pars anterior (top panel) and for the trapezius pars ascendens (bottom panel) for one right-handed subject during the different grasping tasks. Conventions as in Fig. 4.

in the modulation (amplitude and duration) existed between the objects.

A second step in the analysis of these EMG patterns has been done normalizing the timescale of the reaching phase and dividing these period in four time spans (incremental or sliding). In Figs. 4 and 5, the muscle activation intervals are given for one left and one right-handed subject, respectively. The use of four colors (rest in white and three levels of EMG activation in light gray, gray, and black) allows an easy representation of the different muscle activities.

Different timings and levels of activation of the muscles can be observed as a function of the positions of the objects and of the grip types. The timing activation of tripceps brachii caput longum and extensor carpi radialis for one left-handed subject (see Fig. 4 top) is quite similar during the grasping of two objects (key and tennis ball) starting from positions L, C, and R. On the contrary, different EMG timings were produced during the grasping of the can. Looking at the myoelectric activity of the same muscles, it is possible to appreciate differences during the grasping of the objects according to the final position. In fact, different activation times can be observed during the first 25% of the reaching movement of the key and the tennis ball (Fig. 4 top) and after the 50% for the can (Fig. 4 bottom).

Similar patterns of activation of the trapezius pars ascendens (timing and level of force) have been obtained by the right-handed subject (see Fig. 5 bottom) during the grasping of the key and of the tennis ball. The analysis of another proximal muscle, like the deltoideus pars anterior (see Fig. 5 top), highlighted more complex EMG patterns. Moreover, the trapezius presented the highest level of activity during the first phase of the reaching, while the deltoid activity is spread after the first 25% of the movement.

The effects of muscles, positions, and objects on activation levels of averaged EMG signals (as in Figs. 4 and 5) during reach-to-grasp movements have been evaluated using a 3-way ANOVA with a Bonferroni post hoc correction (see Table II). In this table, only the multiple comparisons that are not significant were reported in order to facilitate readability.

Even if after ANOVA test, statistical differences between muscles, positions, and objects seemed to exist, *post hoc* analysis demonstrated that only a limited subset was really different. Considering the muscles, some of them are similar from a statistical point of view (e.g., m2 and m4 for subject 3 or m1, m3, and m6 for subject 6) but without a clear trend. In fact, "simple" reaching movements can be performed by using different muscle strategies by different subjects. This could be due to the musculoskeletal redundancy of the upper limb. At the same time, from the multiple comparisons between positions, it seems that they cannot be discriminated. Finally, interesting remarks can be highlighted about objects. In fact, for four of the six subjects (s3–s6), the three objects were statistically different. Moreover, this is also true for the first two subjects (s1–s2) if bigger time spans were used (i.e., 0–75% and 0–100%).

TABLE II
STATISTICAL ANALYSIS BY MEANS OF 3-WAY ANOVA AND POST HOC BONFERRONI TEST ON EMG LEVELS OF ACTIVATION

Subject1	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	***	***	***	***	***	***	***	***
Positions	NS	**	***	***	NS	***	***	***
Objects	***	***	***	***	***	***	***	***
Posthoc NS only	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
mus	1-2-3,1-6	1-3-4,1-6	1-3-4,2-5	3-4	1-2-3,1-6	1-4	3-4,3-5	1-6
Positions	x	L-C,L-R	L-C	L-C	x	L-R	L-C	L-C
Objects	C-B	C-B	-	-	C-B	-	C-K	B-K
Subject2	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	***	***	***	***	***	***	***	***
Positions	***	***	***	***	***	***	***	***
Objects	***	***	***	***	***	***	***	***
Posthoc NS only	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
mus	1-2,2-4-6	1-4-6,2-5	1-6	1-4-6	1-2,2-4-6	4-6	-	1-6
Positions	C-R	-	-	-	C-R	L-R	-	L-C
Objects	B-K	B-K	-	-	B-K	B-K	C-K	C-K
Subject3	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	***	***	***	***	***	***	***	***
Positions	***	***	***	***	***	***	***	***
Objects	***	***	***	***	***	***	***	***
Posthoc NS only	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	2-4-5, 3-6	2-4	2-4	2-4	2-4-5,3-6	2-3-4	3-4	-
Positions	C-R	C-R	C-R	C-R	C-R	L-R,C-R	L-C	L-R
Objects	-	-	-	-	-	C-B	-	-
Subject4	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	***	***	***	***	***	***	***	***
Positions	***	**	NS	**	***	**	**	***
Objects	***	***	***	***	***	***	***	***
Posthoc NS only	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	1-2	1-2,2-5	3-5	3-5	1-2	-	2-6,3-5	1-3,2-6,3-5
Positions	L-C	C-R	x	L-C,C-R	L-C	L-R	C-R	L-C
Objects	B-K	-	-	-	C-B	-	-	-
Subject5	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	***	***	***	***	***	***	***	***
Positions	***	**	NS	***	***	NS	***	***
Objects	***	***	***	***	***	***	***	***
Posthoc NS only	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	1-3-6	1-3-6	1-3,5-6	1-3	1-3-6	1-3-5	1-3-6	-
Positions	C-R	C-R	x	-	C-R	x	L-R	L-R
Objects	-	-	-	-	-	B-K	-	-
Subject6	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	***	***	***	***	***	***	***	***
Positions	NS	***	***	***	NS	***	***	***
Objects	***	***	***	***	***	***	***	***
Posthoc NS only	0-25	0-50	0-75	0-100	0-25	25-50	50-75	75-100
Muscles	2-4,3-6,5-6	1-2,3-6	2-3,4-5	2-3	2-4,3-6,5-6	1-3,2-3,4-5	1-6	-
Positions	x	L-R	L-R	L-R	x	L-R	L-C,C-R	L-C
Objects	-	-	-	-	-	B-K	-	-

Significant differences between muscles, positions, or objects are indicated (significant: ** if $P < 0.01$; *** if $P < 0.001$; NS: no significant differences). In the post hoc analysis with Bonferroni correction for multiple comparisons, only nonsignificant differences are reported. Muscles; 1 = biceps brachii caput longum, 2 = deltoideus pars anterior, 3 = extensor capi radialis, 4 = flexor capi radialis, 5 = trapezius pars ascendens, and 6 = triceps brachii caput longum; Positions: L, C, and R; Objects: C = can, B = tennis ball, and K = key.

The myoelectric activities of all the muscles were compared during the different reach-to-grasp movements and for the different time spans using a similarity index (see Figs. 6 and 7). The left-handed subject (see Fig. 6) showed very similar values of the index between the grips of the can and the ball independently from the final position in the plane. At the same time, the muscular activities during the grasp of the key are very different with respect to the activities during the grasp of the other objects (high values of the similarity index). A significant different behavior has been seen in the right-handed subject (see Fig. 7). In this case, grips are different among them (high values of the similarity index) and small similarity indexes have been found only between the can and the ball using larger time spans (e.g., 0%–100% panel a) or the second part of the reaching phase (e.g., 50%–75% and 75%–100% panel b).

IV. DISCUSSION

In this study, a statistical analysis was used to show that, in able-bodied subjects, there are distinct patterns of arm muscle EMGs related to grasp of different objects without additional information from most of the hand muscles. This is probably due to the fact that the actions necessary to reach and grasp an object can be seen as a single task where the activations of all the proximal and distal muscles of the upper limb and the hand are simultaneously controlled by the central nervous system in

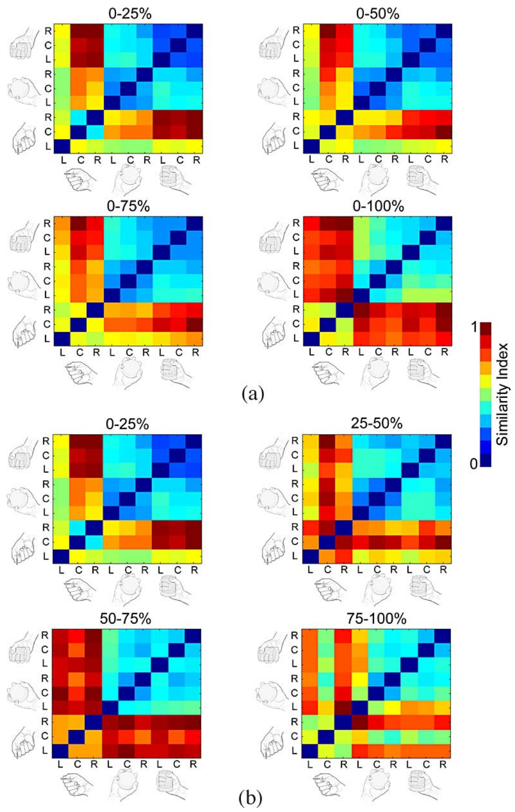

Fig. 6. Similarity of n-dimensional muscle vectors (NDMVs) calculated for the different time spans. Each dimension corresponds to the averaged and normalized activity for each of the six muscles (trapezius pars ascendens, deltoideus pars anterior, biceps brachii caput longum, triceps brachii caput longum, flexor carpi radialis, and extensor carpi radialis). In these similarity matrices, color code indicates Euclidian distance between every possible pair of NDMVs calculated for every position (L, C, and R) and object (can, tennis ball, and key). Highest values in red refer to lowest level of similarity and vice versa. Data from a left-handed subject.

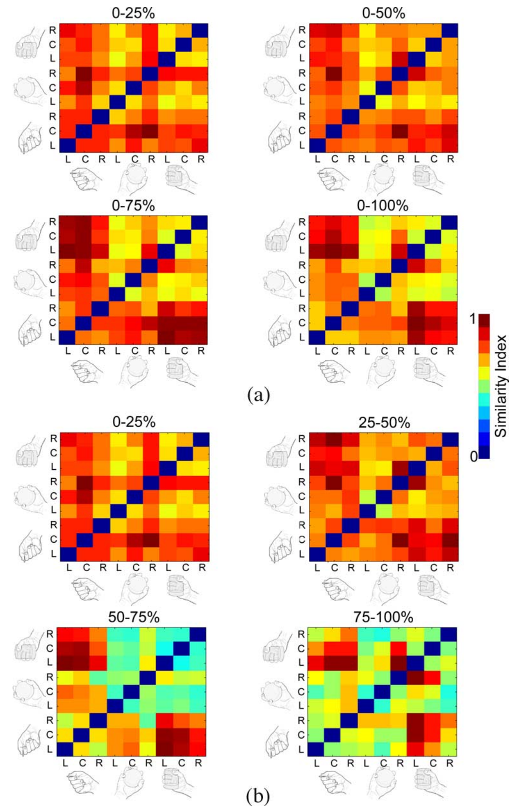

Fig. 7. Similarity of n-dimensional muscle vectors (NDMVs). Data from a right-handed subject. Conventions as in Fig. 6.

a smooth and feedforward way. The design of the experiment was such as to require the subjects to perform reach-to-grasp movements for different objects placed in different locations. Our aim was to try to understand how this repertoire of different grasps is reflected in the activity of a representative sample of arm muscles. The subjects were asked to grasp a given object in the same way. No particular hypothesis was done about the grip force exerted by the subject for each object because no recording was done after the grasping of the object.

The results shown in this paper seem to confirm, in most of the cases, the presence of distinct arm EMGs patterns related to grasp of different objects. The modulation of proximal muscles is different when the type and/or the position of the object to be grasped are changed (see Figs. 4 and 5) both for right-handed and left-handed subjects. Moreover, these differences could allow to identify the kind of grip to be performed, as shown in Figs. 4 and 5 and Table II. This is more evident when the objects are quite different as the key and the cylinder while the similarity is bigger for objects grasped in a more similar way.

In most cases, some muscles showed a statistically significant difference in terms of activation for different objects (see Table II) even if, in some cases, no more than two positions are discriminable.

A period between the 25% and the 50% of the reaching time seems to be sufficient to obtain statistical differences between the three grips used to grasp the can, the tennis ball, and the key.

There are several possible sources of variability in the EMG pattern. Even if particular attention has been devoted to be sure that the subjects used the same consistent grasp posture for a given object, it is not possible to exclude some variability in the actual movement produced and posture adopted to perform the task. These changes in hand postures are likely to result in significant variations in EMG activity because they also affect the intersegmental interaction torques [35].

The findings shown in this paper could also allow the development of different EMG-based strategies to control artificial hands [36]–[41] aimed at replacing the function of the natural ones lost because of an amputation. In fact, even if able to provide interesting results [9]–[16], [42], current EMG-based strategies for the control of prostheses (after limb amputation) are limited by the need for coding the different actions of the artificial device because it is not possible to use the homologous muscles to control the movements of the prosthetic device. For this reason, in the recent past, some groups have tried to develop alternative methods useful to restore some similarity with the natural control scheme. For example, Kuiken and colleagues developed a new method based on the transferring of residual nerves of amputees to other muscles in or near the residual limb [43]. This approach has the interesting advantage that the nerve function correlates physiologically to the function it is controlling in the prosthesis, and therefore, operation is more natural, and thus, easier than current control paradigms. However, it requires a surgical intervention for nerve transplantation. The possibility of using the natural modulation of more proximal muscles during reach-to-grasp tasks to control hand prostheses could represent an interesting solution. For this reason, the possibility of developing an EMG-based control strategy seems to be particularly interesting.

Considering that the average time for the execution of the grips toward the three objects is about 1 s and that a time span bigger than the 25% of the reaching phase is sufficient to have statistical differences between the grips, there is sufficient time for the eventual control of a robotic hand.

In the near future, specific efforts will be carried out to understand the potential of this new approach in terms of number of grip types that can be discriminated, robustness of the performance, extension of these findings with amputees, and intersubject variability.

V. Conclusion

This study suggests that the patterns of EMG activation in arm muscles can provide a reliable representation of motor behavior during reaching and grasping of different objects. This type of information is of critical importance for the interpretation of central mechanisms controlling grasp and it could be used in the future to develop a more "natural" EMG-based approach to control dexterous hand prostheses. It will be very important to investigate the potential and limit of this approach in thenear future.

References

[1] J. Fan, J. He, and S. H. Tillery, "Control of hand orientation and arm movement during reach and grasp," *Exp. Brain Res.*, vol. 171, pp. 283–296, 2006.

[2] M. Jeannerod, "The timing of natural prehension movements," *J. Mot. Behav.*, vol. 16, no. 3, pp. 235–254, 1984.

[3] M. Jeannerod, "The formation of finger grip during prehension. A cortically mediated visuomotor pattern," *Behav. Brain Res.*, vol. 19, no. 2, pp. 99–116, 1986.

[4] J. Marotta, W. Medendorp, and J. Crawford, "Kinematic rules for upper and lower arm contribution to grasp orientation," *J. Neurophysiol.*, vol. 90, pp. 3816–3827, 2003.

[5] R. Marteniuk, J. Leavit, C. MacKenzie, and S. Athenes, "Constraints on human arm movement trajectories," *Can J. Psychol.*, vol. 41, pp. 365–378, 1987.

[6] M. Desmurget, C. Prablanc, M. Arzi, Y. Rossetti, Y. Paulignan, and C. Urquizar, "Integrated control of hand transport and orientation during prehension movements," *Exp. Brain Res.*, vol. 110, no. 2, pp. 499–509, 1996.

[7] T. Brochier, R. Spinks, M. Umilta, and R. Lemon, "Patterns of muscle activity underlying object-specific grasp by the macaque monkey," *J. Neurophysiol.*, vol. 92, no. 3, pp. 1770–1782, 2004.

[8] C. Elsinger and D. Rosenbaum, "End posture selection in manual positioning: Evidence for feedforward modeling based on a movement choice method," *Exp. Brain Res.*, vol. 152, no. 4, pp. 499–509, 2003.

[9] B. Hudgins, P. Parker, and R. Scott, "A new strategy for multifunctional myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 1, pp. 82–94, Jan. 1993.

[10] W. J. Kang, J. R. Shiu, C. K. Cheng, J. S. Lai, H. W. Tsao, and T. S. Kuo, "The application of cepstral coefficients and maximum likelihood method in EMG pattern recognition," *IEEE Trans. Biomed. Eng.*, vol. 42, no. 8, pp. 777–785, Aug. 1995.

[11] S. Micera, A. M. Sabatini, and P. Dario, "A hybrid approach to EMG pattern analysis for classification of arm movements using statistical and fuzzy techniques," *Med. Eng. Phys.*, vol. 21, no. 5, pp. 303–311, 1999.

[12] M. Zecca, S. Micera, M. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Crit. Rev. Biomed. Eng.*, vol. 30, no. 4–6, pp. 459–485, 2002.

[13] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–854, Jul. 2003.

[14] A. Ajiboye and R. Weir, "A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 3, pp. 280–291, Sep. 2005.

[15] A. Chan and K. Englehart, "Continuous myoelectric control for powered prostheses using hidden Markov models," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 1, pp. 121–124, Jan. 2005.

[16] M. Oskoei and H. Hu, "Myoelectric control systems—a survey," *Biomed. Signal Proc. Control J.*, vol. 2, pp. 275–294, 2007.

[17] J. Rosen, M. Brand, M. Fuchs, and M. Arcan, "A myosignal-based powered exoskeleton system," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 31, no. 3, pp. 210–222, May 2001.

[18] K. Kiguchi, K. Iwami, M. Yasuda, K. Watanabe, and T. Fukuda, "An exoskeletal robot for human shoulder joint motion assis," *IEEE/ASME Trans. Mechatronics*, vol. 8, no. 1, pp. 126–136, Mar. 2003.

[19] K. Farry, I. Walker, and R. Baraniuk, "Myoelectric teleoperation of a complex robotic hand," *IEEE Trans. Robot. Autom.*, vol. 12, no. 5, pp. 775–788, Oct. 1996.

[20] O. Fukuda, T. Tsuji, M. Kaneko, and A. Otsuka, "A human-assisting manipulator teleoperated by EMG signals and arm motions," *IEEE Trans. Robot. Autom.*, vol. 19, no. 2, pp. 210–222, Apr. 2003.

[21] C. Choi, S. Micera, J. Carpaneto, and J. Kim, "Development and quantitative performance evaluation of a noninvasive EMG computer interface," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 1, pp. 188–191, Jan. 2009.

[22] I. A. Kapandji, *The Physiology of the Joints: Annotated Diagrams of the Mechanics of the Human Joints*. New York: Churchill Livingstone, 1982.

[23] E. V. Biryukova, A. Roby-Brami, A. A. Frolov, and M. Mokhtari, "Kinematics of human arm reconstructed from spatial tracking system recordings," *J. Biomech.*, vol. 33, no. 8, pp. 985–995, 2000.

[24] S. M. Michaelsen, S. Jacobs, A. Roby-Brami, and M. F. Levin, "Compensation for distal impairments of grasping in adults with hemiparesis," *Exp. Brain Res.*, vol. 157, no. 2, pp. 162–173, 2004.

[25] J. Carpaneto, S. Micera, G. Galardi, A. Micheli, M. Carboncini, B. Rossi, and P. Dario, "A protocol for the assessment of 3d movements of the head in persons with cervical dystonia," *Clin. Biomech.*, vol. 19, no. 7, pp. 659–663, 2004.

[26] S. Micera, J. Carpaneto, F. Posteraro, L. Cenciotti, M. Popovic, and P. Dario, "Characterization of upper arm synergies during reaching tasks in able-bodied and hemiparetic subjects," *Clin. Biomech.*, vol. 20, no. 9, pp. 939–946, 2005.

[27] J. Basmajian and A. Blumenstien, *Eletrode Placement in EMG Biofeedback*. Baltimore, MD: William & Wilkins, 1980.

[28] J. F. Cram and G. S. Kasman, *Introduction to Surface Electromyography*. Gaithersburg, MD: Aspen, 1998.

[29] A. Sabatini, "Identification of neuromuscular synergies in natural upper-arm movements," *Biol. Cybern.*, vol. 86, no. 4, pp. 253–262, 2002.

[30] M. Benedetti, P. Bonato, F. Catani, T. D'Alessio, M. Knaflitz, M. Marcacci, and L. Simoncini, "Myoelectric activation pattern during gait in total knee replacement: Relationship with kinematics, kinetics, and clinical outcome," *IEEE Trans. Rehabil. Eng.*, vol. 7, no. 2, pp. 140–149, Jun. 1999.

[31] G. Staude, C. Flachenecker, M. Daumer, and W. Wolf, "Onset detection in surface electromyographic signals: A systematic comparison of methods," *EURASIP J. Appl. Signal Process.*, vol. 2001, no. 2, pp. 67–81, 2001.

[32] P. W. Hodges and B. H. Bui, "A comparison of computer-based methods for the determination of onset of muscle contraction using electromyography," *Electroencephalogr. Clin. Neurophysiol.*, vol. 101, no. 6, pp. 511–519, 1996.

[33] S. Micera, A. M. Sabatini, and P. Dario, "An algorithm for detecting the onset of muscle contraction by EMG signal processing," *Med. Eng. Phys.*, vol. 20, pp. 211–215, 1998.

[34] A. V. Poliakov and M. H. Schieber, "Limited functional grouping of neurons in the motor cortex hand area during individuated finger movements: A cluster analysis," *J. Neurophysiol.*, vol. 82, no. 6, pp. 3488–3505, 1999.

[35] W. Darling and K. Cole, "Muscle activation patterns and kinetics of human index finger movements," *J. Neurophysiol.*, vol. 63, pp. 1098–1108, 1990.

[36] P. Kyberd and P. Chappell, “The Southampton hand: An intelligent myoelectric prosthesis,” *Med. Eng. Phys.*, vol. 31, no. 4, pp. 326–334, 1994.
[37] C. Light and P. Chappell, “Development of a lightweight and adaptable multiple-axis hand prosthesis,” *Med. Eng. Phys.*, vol. 22, no. 10, pp. 679–684, 2000.
[38] M. Carrozza, F. Sebastiani, C. Suppo, B. Massa, F. Vecchi, R. Lazzarini, M. Cutkosky, and P. Dario, “The development of the spring hand: A self-adaptive hand prosthesis for restoring natural grasping,” *Auton. Robots*, vol. 16, no. 2, pp. 125–141, 2004.
[39] T. Laliberte and C. Gosselin, “Simulation and design of underactuated mechanical hands,” *Mech. Mach. Theory*, vol. 33, no. 1–2, pp. 39–57, 1998.
[40] B. Massa, S. Roccella, M. C. Carrozza, and P. Dario, “Design and development of an underactuated prosthetic hand,” presented at the 2002 IEEE Int. Conf. Robot. Autom., Detroit, MI, May 1999.
[41] *MYOBock-Arm Components 1997/98,* Duderstadt, Germany: Otto Bock Orthopedic Industry GmbH, 1998.
[42] D. Nishikawa, Y. Ishikawa, W. Yu, M. Maruishi, I. Watanabe, H. Yokoi, Y. Mano, and Y. Kakazu, “On-line learning based EMG prosthetic hand,” in *Electrophysiology and Kinesiology*, Y. Mano, *et al.*, Ed., Bologna, Italy: Monduzzi Editore, 2000.
[43] L. Miller, K. Stubblefield, R. Lipschutz, B. Lock, and T. Kuiken, “Improved myoelectric prosthesis control using targeted reinnervation surgery: A case series,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 1, pp. 46–50, Feb. 2008.

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