On the development of a new EMG–controlled robot-mediated protocol for post-stroke neurorehabilitation

B. Cesqui, H.I. Krebs, and S. Micera, *Member, ISG*

Abstract— **The goal of our work is to explore the use of EMG signals for post-stroke, robot-mediated therapy. Previous findings suggest that providing performance feedback to the users could enhance recovery beyond simple knowledge of success or failure in task completion. We are exploring whether activation of arm muscles can be used to a) generate goal-directed movements and b) provide the required performance feedback to enhance recovery. The EMG-based scheme must be able to determine the subject's intended directions within a few hundred milliseconds. Here we report a pilot study involving young, healthy subjects conducted to determine whether it is possible to build a static map to cluster EMG activation patterns for horizontal reaching movements.**

I. Introduction

Robot mediated, sensory motor therapy has shown positive results in augmenting recovery of stroke patients [1, 2]. Optimizing and tailoring therapy to a patient's needs is one of the most important issues addressed by research groups [3, 4]. Cirstea and Levin [5] asserted that therapies stimulating patient attention to the movements themselves in addition to the outcomes are more effective; furthermore, they might facilitate better generalization of motor skills to novel situations. At this time, we are investigating the use of electromyographic (EMG) signals to control the movement of a robotic system during neurorehabilitation in order to provide some movement feedback and to correlate the activation of arm muscles with the generation of reaching movements. The EMG signal is directly generated by the brain and is always activated before the beginning of an action; thus, it can be used in real time applications because it is possible to predict the movement before it happens.

Similar problems have been treated by different research groups in the past [6-8]. Typical applications are related to prosthetic hand control, grasp recognition and human computer interaction [9-11]. Using a different approach from these applications, we aimed at developing a feedforward model depending on which part(s) of the Central Nervous System of normal healthy subjects initiates the movements, i.e., to map a number of different goals into a set of muscles patterns. In fact, if this general model exists, it could be reasonable both to use it for robotic aid therapy and also to compare this paradigm with performances of stroke patients who have lost the capability of modulating their muscle activation. It is noteworthy then that this model must not be affected by intra- and inter-subjects variability or by repeatability of the measure (due to posture on the robot, positioning of the electrodes, or different experimental conditions). To this aim. it is necessary to develop an algorithm able to identify the intended movement direction from EMG signals (even with weak muscular activity) and provide a corrective action if appropriate. The outcomes of this preliminary study with healthy subjects will be used to assess feasibility and quality of the signal classifier. We compared two different methods for pattern recognition: a more classical approach using statistical learning tools (Support Vector Machine), and a second graphical approach that explores EMG spatial characteristics, detects anomalies, and interprets co-activation patterns as related to posture, arm stabilization, or high speed motion.

II. Methods

A. Experiment Protocol

Nine right-handed young healthy subjects (age range between 24-44 years old) were involved in the experiment after providing written informed consent. Participants sat on a chair and grasped the handle of a planar manipulandum, the Inmotion2 (Interactive Motion Technologies, Cambridge, MA, USA); the trunk was restrained by a belt to minimize movements and the right elbow was supported on the horizontal plane. Participants were instructed to make point-to-point reaching movements between a central position and one of the four peripheral locations arranged in the form of a cross of 14 cm distance from the center to the outbound target. After one second, they were prompted by a sound to initiate movement. Movements were performed with three different time intervals, 300-600-1000ms. Subjects were alerted if they went too slow or too fast by visual feedback. Each direction and condition was repeated 5 times.

B. Data Acquisition

Hand position and EMG activity of 7 muscles were recorded. The robot sampled hand position at 1000 Hz. In all experiments, we recorded the EMG activity of biceps (BI), triceps(TRI), middle, posterior, and anterior deltoid (DM,PD,PA), pectoral (PE) and trapezium (TRA) with

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Benedetta Cesqui is with the IMT Alti Studi Lucca Complesso S. Micheletto Via San Micheletto 3 55100 (e-mail benedetta.cesqui@imtlucca.it).

Silvestro Micera is with the ARTS and EZ Laboratories, Scuola Superiore Sant'Anna viale R. Piaggio 34,56025 Pontedera, Italy (e-mail micera@sssup.it).

H I Krebs is with the Newman Lab, Department of Mechanical Engineering, MIT Massachusetts Institute of Technology, 77 Massachusetts Ave, Cambridge, MA, USA 02139 (e-mail hikrebs@mit.edu) and with the Department of Neurology and Neuroscience of the Weill Medical College of Cornell University. HI Krebs is a co-inventor in the MIT held patent for the robotic device used in this work. He holds equity positions in Interactive Motion Technologies (Cambridge, MA, USA) the company that manufactures this type of technology under license to MIT.

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bipolar surface electrodes (Bagnoli-16, Delsys, Boston, MA), where the EMG signal was bandpass filtered (20–450 Hz) and amplified (gain of 1000).

C. *Data Analysis*

For each movement, we selected as its EMG baseline the signal between the beginning of the trial and the instant in which subjects were prompted to move (beep). Movement onset was computed considering the instant in which hand speed passed the 5% mark of its maximum speed. EMGs signals were analyzed in a time window between [-100 100] ms with respect to movement onset. Two different methods were used to cluster the data; the first one allowed a graphic clusterization and was called biomechanical model, while the second exploited the statistical distribution of the data to separate the different classes (Support Vector Machine). We used the EMG raw data of each movement to determine the Coefficient of Expressiveness (COE) [12], and EMG Histogram parameter (HIST) [13].

CoE Parameter

The PCA analysis was computed for each movement and applied to the covariance matrix of the EMG raw signals considered for the specified time window.

The CoE parameter was computed for each l^{th} muscle, r^{th} direction based on the following expression:

$$k_{j,l,r} = \sum_{i=1}^{n} \left| c_{i,l,r} \right| \frac{\lambda_i}{\sum_{m=1}^{p} \lambda_m} \qquad j=1,\ldots,J \qquad (1)$$

where n is the number of Principal Components that contains 80% of the variance of the system, $c_{i,l,r}$ is the correlation coefficient between the i^{th} PC and the selected muscle for the r^{th} movements, λ_i is the eigenvalue associated to the i^{th} PC, p is the total number of eigenvalue, J is the numbers of trials.

For each movement the CoE coefficients were normalized with respect to their maximum value among the 7 muscles; only values larger than 0.7 were considered important, the others were considered non-relevant (CoE=0). Each trial was summarized via the 7-component vector.

HIST Parameter

The HIST parameter was computed fixing a voltage range for each muscle activation symmetric with respect to the baseline, which includes the activity for all conditions and directions. The interval was divided into 9 bins. The frequency with which the EMG voltage falls within each of the voltage bins was computed; therefore, in the end each muscle was represented by a set of 9 values and the entire movement by a vector of 63 components.

1) Biomechanical Model (BM)

The CoE Parameter was used to cluster the data according to the geometry. Flanders [14, 15] and Georgopoulus [16] suggested that EMG signals for a particular muscle could be decomposed into a phasic and a tonic waveform for all directions in a single plane. These two components were then time-shifted and amplitude-scaled according to movement direction. Thus, each muscle was:

1) considered more relevant for a direction when the CoE parameter >0.7; i.e.,, it acted as an agonist;
2) not activated in the opposite movement direction, in which it played the role of the antagonist.

Figure 1B shows the activation map for all conditions and subjects. We clustered together muscles responsible for particular movement direction (Muscle, CoE). The results suggest 4 different zones (see Figure 2). Thus, recognition of movement direction was possible provided we could identify the muscle activation zone. Incorrect pattern recognition was due to overlapping zones, due to co-contraction of agonist and antagonist muscles to stabilize the arm, and due to differences in the initial posture and speed. To account for all these factors, we developed a cost function based on literature review of abnormal coactivation patterns [15, 16]. We were then able to detect and interpret all the anomalies.

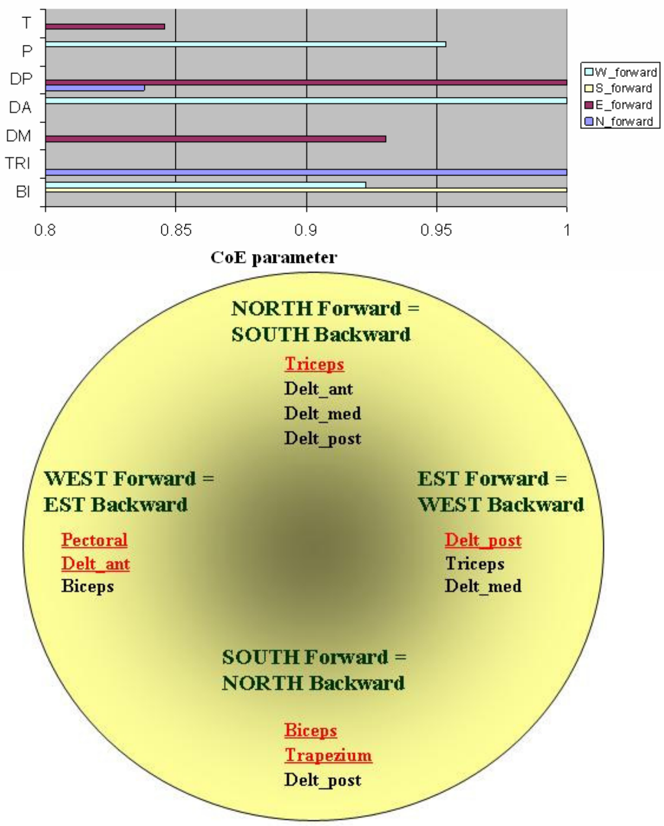

Figure 1 A) Top: An example of CoE for forward movement direction towards the robot (robot is located in front of the subject) B) Bottom: muscle activation map; in red are the most important muscles for the particular direction.

2) Support Vector Machine (SVM)

The different values of the HIST parameter were used as inputs for a Support Vector Machine algorithm (kernel: Gaussian radial basis function, sigma=2), a supervised learning method used for classification and regression [17, 18].

To validate the model many different tests were carried out; in each case the SVM was trained with the 70% of the available data and validated with the remaining 30%.

a) Training and validating individually with the data of each subject
b) Training and validating with the composite data of all subjects
c) Training with 7 subjects and validating with the 2 worst performers (higher number of anomalies)

3) SVM+ BM

We considered the integration of the two methods. The integrated pattern recognition system ran the data three separate times and, like a voting system, selected the direction recognized more frequently (at least 2/3). The integrated system ran the SVM with different time windows (I interval [-100 100] ms, II interval [0,50] ms), and the BM. We tested the hybrid system with sets of 5 patients randomly selected from the data.

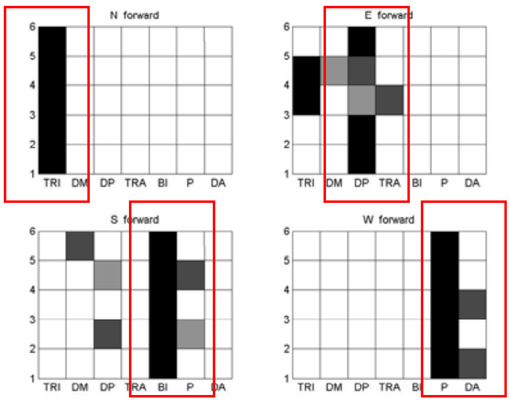

Figure 2 - Distribution of the CoE parameter (Muscle, CoE) of one subject in the different movement directions. Figure showed the presence of 4 defined muscle activation zones.

Intra-subject variability was also evaluated for data collected during different days for the same subject (4 out of 7 subjects). Furthermore, the model was re-designed with a smaller subset of subjects (5 to 7) to understand how the number of training data points can affect the accuracy of the SVM.

III. RESULTS

Table I summarizes the results of the tests carried out with both methods. We speculate that differences in forward and backward movements are due to the small differences in initial posture. In the case of the BM, the forward rate of success increased from 67.5% to 80% considering a muscle pattern of activations involving both the agonist and antagonist muscles. As expected, employing the SVM and training it individually led to a high rate of success (mean value 95%), but it dropped to 89% when training with the "composite" of all subjects. During validation with the 2 subjects characterized by the worst performance, the rate of success dropped further (mean value of 83%). The integrated voting system increased the success rate to 86%. Experiments conducted in different days with the same subjects showed that, in the case of forward movements, there was no significant intra-subject variability.

Table II showed an overall review of our main results obtained with different techniques against literature research. It was able to get the 100% of accuracy using a neuro-fuzzy classifier to detect arm movements in three directions (excluding our South direction) [12]. Of notice, he considered different features for different subjects were considered and the classification algorithm has beed trained his algorithm individually [12]. Other research groups investigated alternatives for EMG control of prosthetic devices [9-11]. The classifiers were trained individually with a resulting success rate varying between 94-99%. Hidden Markov Models (HHM) and Higher Order Statistics (HSO) were also tested [19, 20], but the results so far were not very promising, having relatively low success rates. Finally, brain computer interfaces (BCI) used to command computer devices with muscle activity of upper limbs were also considered [21]. They claimed a remarkable 96-97% recognition of individual intentions. We were only able to achieve similar success when we tuned the system for the specific individual.

TABLE I
RESUME OF THE SUCCESS RATE OBTAINED WITH THE BIOMECHANICAL AND SVM METHODS PROPOSED IN THIS PAPER

Methods	Forward %	Backward %
Biomechanical Model (BM)	67.5%	63%
BM with cost functions	80%	65%
SVM individual training	95 % ± 10%	87% ± 11%
SVM composite of all subjects	89 % ± 4%	80% ± 6%
SVM composite of 7 subjects vs 2 medium subjects	86% ±7%	79% ± 6%
SVM composite of 7 subjects vs 2 outliers*	83% ± 7%	79% ± 9%
SVM + BM (composite of 7 subjects vs 2 outliers*)	86% ±7%	80% ±11%
Intra-subject Reliability (Same subject in different days)	No significant differences	Significant differences
SVM (composite of 5 subjects vs 2 outliers)	83.1% No differences with *	79% No difference with *

IV. DISCUSSION

This pilot study involving young healthy subjects was conducted with the aim of understanding whether it was possible to build a static map of EMG pattern activation for point-to-point reaching movements. We limited the data to the initial 100ms of movement and tried to predict the ultimate direction of movement. We also attempted to determine inter and intra-subject variability and how it could affect repeatability. In the end, our best classifier guessed correctly at a rate of 86%. This result might look inferior to other groups (see Table II) but, in point of fact, we claim that our approach is more realistic for our application. Most of the cited results achieved a higher success rate through individual training and validation employing data from the same subject. We employed data from distinct subjects during validation. Furthermore, we considered different hand speeds and did not exclude any data to determine success rate.

Inter- and intra-subject variabilities were not the most critical factors affecting the classifier performance. It appears to be possible to define a general map of pattern activations: muscles responsible for movements in a particular direction were always the same, albeit there were some occasional outliers due to co-activation, due to arm stabilization or posture.

TABLE II
LITERATURE SEARCH FOR EMG PATTERN RECOGNITION

Methods	Accuracy range
Arm planar movement using statistical and fuzzy techniques (7 shoulder muscles, arm movement in 3 direction; neuro-fuzzy classifier; calibration of the classifier and feature of signals chosen depending on the subject)	100%
Arm prosthesis EMG based control (arm and forearm muscles, several NN and fuzzy classifiers, distinct features individually calibrated)	94-99%
Other methods for EMG classification (HHM, HSO)	90-94%
Brain computer interface (BCI) using EMG	96-97%

The rate of success of the SVM and BM were comparable, except when SVM was trained to fit a single subject: in that case, SVM approach was clearly superior. However, we failed to guarantee 100% success with any method, SVM, BM, or the integrated voting method. The SVM attempts to classify based on the geometric characteristics of the distribution; it needed to be trained before deployment and its performance depends heavily on the quality of the training data. We suspect that 100% success could not be achieved employing a single model: the system must be individually tuned for each subject. This is not a practical approach for patients with high injury level who might not be able to hit all the targets.

The BM approach was able to characterize and quantify muscle activity in a spatial way and to provide a graphical overview of the variations among different directions. It seems to cope better with anomalies. To generate a universal model not tuned on a specific subject, the BM might be advantageous since it is less complex and reduces significantly the computation time. It also copes better to detect co-activation spurious EMG. Thus, the BM will soon pass through further analysis with stroke patients during robot-mediated rehabilitation therapy.

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