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Biomimetic NMES controller for arm movements supported by a passive exoskeleton*

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Abstract— **The European Project MUltimodal Neuroprosthesis for Daily Upper limb Support (MUNDUS) aims at the development of an assistive platform for recovering direct interaction capability during daily life activities based on arm reaching and hand functions. Within this project the present study is focused on the design of a biomimetic controller able to modulate the neuromuscular electrical stimulation needed to perform reaching movements supported by a commercial passive exoskeleton for weight relief.**

Once defined the activities of daily life to be supported by the MUNDUS system, an experimental campaign on healthy subjects was carried out to identify the repeatable kinematics and muscular solution adopted during the target movements. The kinematics resulted to be highly stereotyped, a root mean squared error lower than 5° was found between all the trajectories obtained by healthy subjects in the same movement. A principal component analysis was performed on the EMG signals: less than 5 components explained more than the 85% of the signal variance. This result suggested that the muscular strategy adopted by healthy subjects was stereotyped and can be replicated by a biomimetic NMES controller. The controller was based on a time-delay artificial neural network which mapped the dynamic and non-linear relationship between kinematics and EMG activations to determine the stimulation timing. The stimulation levels reproduced the same scaling factors found between muscles in the stereotyped strategy. The controller was tested on 2 healthy subjects and though it was a feedforward controller, it showed good accuracy in reaching the desired target positions. The integration of a feedback controller is foreseen to ensure the complete accomplishment of the task and to compensate for unpredictable conditions such as muscular fatigue.

I. Introduction

MUNDUS is an assistive framework for recovering interaction capability of severely impaired people based on upper limb motor functions (http://www.mundus-project.eu). Within this project, the present work aimed at integrating a commercial passive exoskeleton for weight support with a Neuro Muscular Electrical Stimulation (NMES) controller for arm movements.

The complex mechanics of the human body associated with its many degrees of freedom (DOF) and its multiple, nonlinear actuators have largely thwarted attempts to find analytical solutions for controlling movements. This is the well-known problem of motor redundancy every day issued by our brain. The infinite possible solutions are solved in a very stereotyped manner by healthy subjects based on the optimal control hypothesis which states that the physiological use of our motor apparatus responds to an optimum exploitation of human motor system to achieve the desired task [1, 2]. In fact, although a broad number of motor solutions are feasible to achieve any task, it has largely showed that a high repeatable kinematic of muscular solutions (stereotypes) are usually observed even for complex movements. This behavior can be explained asserting that any available motor solution has a cost and the central nervous system utilizes an optimal control system to select the minimum cost solution [1]. Starting from this assumption, we can study the physiological muscular strategy during any task and try to mimic it through NMES.

Artificial neural networks (ANN) have been shown to be capable of dealing with the nonlinearities and complex dynamics observed in the neuromuscular system, and several attempts to use them for NMES control can be found in literature [3-5]. These studies demonstrated that an ANN-based controller is capable of generating the appropriate levels of stimulation for muscles involved both in single joint movement or coordinated tasks.

The approach followed in this study can be summarized in three steps. First, user requirements were identified to define the interaction tasks to be supported by the final MUNDUS system. Then, an experimental campaign on healthy subjects was carried out and EMG and kinematics data were analysed to identify a stereotyped strategy adopted during the target reaching movements. Finally, the biomimetic NMES controller based on ANN was designed and tested on healthy subjects.

II. The Definition of Interaction Tasks

To identify the users and clinical requirements a twofold strategy was adopted based on a user-centred approach [6]. A focus group of experts, and end users' interviews were used to identify the possible applications of the MUNDUS system and to assess the willingness of people with disabilities to try out the system. The data collected identified the need for some specific activities of daily life such as drinking with a straw, pressing a button, touching a spot on the body, interacting with objects for personal hygiene, and eating. Starting from these interaction tasks, the following motor tasks were identified: reaching objects placed in 3 different positions on the table and bring them to the mouth; reaching the shoulder from rest position (Fig. 1).

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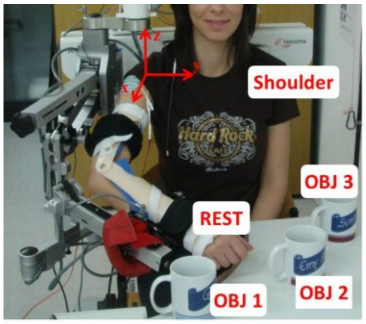

Fig 1: Target movements

III. The Identification of Stereotyped Strategy

A. Experimental Procedure

A passive exoskeleton, shown in Fig.1, (ArmeoSpring®, HOCOMA AG, Switzerland) supported the arm weight during tasks execution and a customized orthosis was used to prevent the prono-supination of the forearm and the wrist flexion/extension, in order to replicate the conditions in which the users will use the final MUNDUS platform. During movements, EMG signals were acquired from the following muscles: biceps, triceps, anterior, medial and posterior deltoid, and trapezius. The potentiometers embedded in the ArmeoSpring measured the angular trajectories of the shoulder elevation in the sagittal plane and the shoulder rotation in the horizontal elevation plane; an electrogoniometer was used to measure the elbow flexion-extension. Attention was paid to ensure the same rest position and objects placement between subjects, in terms of joint angles. Six healthy volunteers were involved in the trials. They repeated 12 times all the interaction tasks.

B. Data Analysis

Each task was divided into sub-actions. The interactions with the objects on the table were divided into 4 sub-actions: (1) reaching the object from the rest position; (2) bringing the object to the mouth; (3) bringing back the object to the table; (4) coming back to rest; while the movement to reach the shoulder was divided into 2 sub-actions: (1) from rest to the body landmark, and (2) back to rest.

The EMG signals were off-line high-pass filtered (5th order Butterworth, cut-off frequency of 10 Hz), full-wave rectified and low-pass filtered (5th order Butterworth, cut-off frequency of 5 Hz). The obtained EMG envelopes were normalized with respect to the EMG recorded during a brief isometric maximal voluntary contraction (MVC). Both normalized EMG profiles and angular trajectories were resampled by a cubic spline to have the same number of samples among all repetitions.

In order to investigate whether a common stereotyped kinematic strategy existed between subjects, for each sub-action, the Root Mean Squared Error (RMSE) between the angular profiles of each subject and the ones obtained by averaging all subjects was computed.

A Principal Component Analysis (PCA) was used to obtain an EMG activation profile per each muscle and sub-action (starting from the 12x6 normalized profiles). If a low number of principle components were enough to explain more than the 80% of the signal variance the profile was defined as stereotyped.

C. Results

The RMSE computed on kinematics data was equal to 4.7° ± 3.1°, a value comparable to the RMSEs obtained by averaging all the trajectories of each subject and to the error of 5° due to the replacement of the rest position and of the objects positions on the table between the subjects. Thus, we concluded that a common stereotyped kinematic strategy existed between the healthy volunteers involved in the experimental campaign.

Concerning the EMG analysis, less than 5 principal components were enough to describe more than the 85% of the variance. In particular, 5 components were required only for muscles characterized by a low activation (less than 5% of the MVC). These results highlighted that the muscular strategy adopted is stereotyped indicating the possibility to replicate it through a biomimetic controller for NMES.

IV. The Biomimetic NMES Controller

A. The Controller Structure

The feedforward biomimetic NMES controller includes the cascade of three components as shown in Fig. 2:

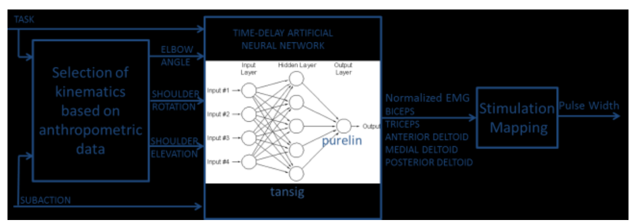

Fig 2: Structure of the biomimetic NMES controller

- The selection of the desired angular trajectory based on the anthropometric data of the user (upper and lower arm lengths). The kinematic data acquired on the 6 healthy subjects were classified into two clusters (women and man cluster in the following). Once measured the anthropometric data of a new subject, the cluster the subject belongs to is identified and the desired angular trajectories are chosen from the data set acquired for training accordingly.
- A time-delay ANN (TDANN) which maps the relationship between kinematics data and EMG activations to determine the stimulation timing (see the following section).
- A stimulation mapping between the TDANN outputs and the stimulation pulse width (PW) levels. For each muscle a scaling factor was used to replicate the proportionality of the activation measured in the different interaction tasks. This means that the scaling factors differ among the different tasks. The scaling factors are multiplied by the maximal PW.

B. The TDANN Design and Optimization

Both static ANN (i.e., current values of muscle activations as the only inputs) and TDANN (i.e., current and previous muscle activations as inputs) were evaluated. Time-delay inputs were considered to capture the spatio-temporal properties of the muscle activations. The number of delays determines how many past values of the input signals should be used as inputs to accurately produce the outputs. This delay value was varied between 0 (static ANN) and 100 ms (5 samples at 50 Hz) and after training different networks a delay of 60 ms was chosen as the best compromise between network performance and real-time application.

The architecture of the TDANN was defined as a 2-layer perceptron having 12 inputs including the 3 kinematic current angles and 3 past values for each input and a maximum 5 outputs (the EMG profiles analyzed using the PCA). The number of outputs resulted to be variable between the different sub-actions. Indeed, when the normalized EMG acquired on all the subjects was less than the 5% of its correspondent MVC, the muscle was considered not active at all and, for that specific sub-action the output was removed from the architecture. We selected 2 outputs, i.e. biceps and anterior deltoid, for the interaction with the shoulder, whereas 3 outputs, i.e. biceps, anterior, and medial deltoid, for the 2 central sub-actions (sub 2-3) of the interactions with the objects. For the other two sub-actions "from rest position to the object" and "from the object to rest", the muscle activation was too low to recognize a reliable stereotyped strategy.

To take into account the physiological delay between the delivery of the stimulation and the movement production, the EMG profiles were shifted backwards about 120 ms with respect to their correspondent kinematic data.

The activation functions were hyperbolic tangent functions in the hidden layer and linear transfer functions in the output layer. The number of neurons used in the hidden layer was varied systematically between 6 and 24 hidden neurons while testing errors were monitored. The goal was to find the smallest architecture capable to provide good performance results. The chosen ANN was the network that minimized the error on data never seen during training [5].

C. Tracking Performance of the Chosen TDANN on the Training and Testing Data Set

Fig. 3 reports an example of the tracking performance obtained during the interaction with Object 2. In particular the comparison between the desired output (the three normalized EMG profiles collected for the TDANN data set) and the 3 corresponding outputs computed by the trained TDANN. The TDANN performance worsened at the beginning and at the end of the sub-action. This can be due to the training set that was defined as the cascade of different repetitions of each sub-action creating relevant gaps between the last sample of one repetition and the first sample of the consecutive one. The performance of the chosen TDANN in each sub-action obtained on the training and testing set was computed in terms of mean and standard deviation of the Mean Squared Error (MSE) obtained separately on each output. The MSE computed averaging all the sub-actions was about 0.076±0.024 on training and 0.017±0.013 on testing sets. Thus, none of the TDANN overfitted on the training data.

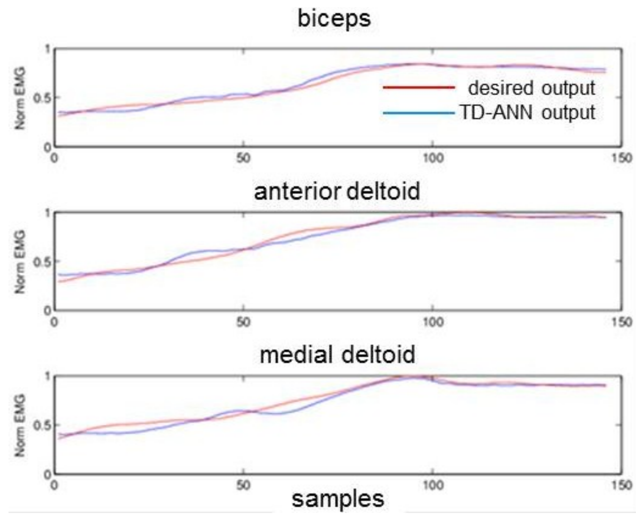

Fig 3: A representative example of the tracking performance obtained by the TDANN optimized for Object 2 sub 2 on the testing input values extracted from the "woman cluster".

D. Experimental Testing on Healthy Subjects

The biomimetic controller was tested on 2 healthy subjects in all the interaction tasks. A current-controlled 8-channel stimulator (RehaStim; Hasomed GmbH) was used and surface electrodes were applied in a bipolar configuration on biceps, medial and anterior deltoid muscles. Rectangular biphasic pulses with a stimulation frequency of 50 Hz were adopted. Before the beginning of the trials the stimulus intensity was set individually for each muscle at a tolerable value producing the maximal range of motion of the corresponding joint with a PW of 500 µs.

In each task tested the subject was asked first to perform the two sub-actions voluntarily without any stimulation. Then 6 repetitions of the two sub-actions were induced by the biomimetic NMES controller. When the biomimetic controller was active the subject was asked not to contribute voluntarily to the movement and the PW was modulated between 100 and 500 µs. The NMES controller maintained the last stimulation value obtained during the first sub-action while waiting for the beginning of the second one.

Given the task, the sub-action, and the anthropometric data, the kinematic inputs to be used as inputs of the TDANN were selected as described in section IV.A. Thus, the biomimetic controller worked only as a feedforward controller and the stimulation profiles just reproduced the pre-learned EMG activations. Fig. 4 shows the results obtained by one subject during a representative task: bringing object 1 to the mouth (sub 2, panels (a) and (c)) and coming back to table (sub 3, panels (b) and (d)). In the upper panels, the angular trajectories induced by NMES and the target points reached voluntarily by the subject are shown; in the lower panels the pulse width delivered to the muscles are reported.

The performance of the controller was evaluated computing the difference between the target point and the position reached through the NMES controller both in terms of the 3 angular DOF and in terms of end effector position. The end effector position was estimated using a kinematic model having the reference frame in the shoulder (Fig. 1) and considering the humeral rotation fixed at 45°.

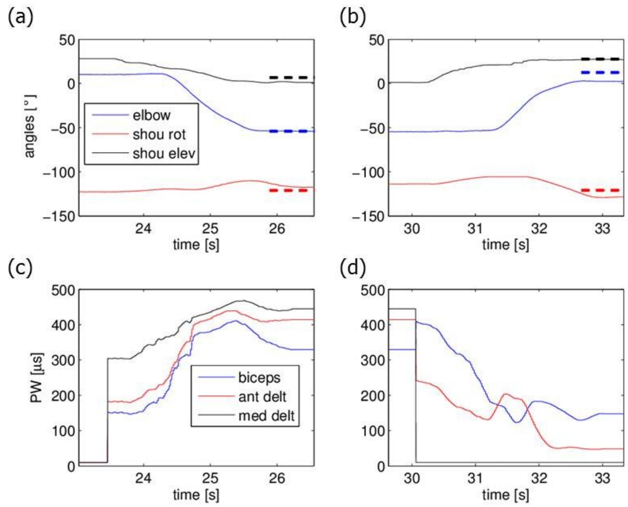

Fig 4: Results obtained by one subject during the execution of a representative task: bringing object 1 to the mouth (panels (a) and (c)) and back to the table (panels (b) and (d)). Panels (a) and (b) show the angular trajectories, while panels (c) and (d) report the pulse width profiles. The dashed horizontal lines indicate the target points reached voluntarily by the subject.

TABLE I. PERFOMANCE OF THE BIOMIMETIC CONTROLLER COMPUTED IN TERMS OF THE DISTANCE BETWEEN THE TRUE TARGET POINT OF EACH SUB-ACTION AND THE FINAL POINT REACHED BY NMES.

	Elbow [deg]	Shou Rot [deg]	Shou Elev [deg]	X [cm]	Y [cm]	Z [cm]
ToShoulder						
Sub 1	37.86 ± 18.78	-4,91 ± 2.66	6.26 ± 2.96	15.20 ± 7.16	14.68 ± 4.68	-13.32 ± 7.10
Sub 2	-8.74 ± 8.16	19.03 ± 9.88	-2.49 ± 1.24	-17.25 ± 5.49	12.15 ± 3.84	6.10 ± 4.60
Object 1						
Sub 2	4.82 ± 3.41	4.65 ± 3.46	-9.59 ± 3.86	-3.24 ± 1.16	1.76 ± 1.41	4.24 ± 1.77
Sub 3	-13.24 ± 6.42	-2.88 ± 5.94	2.79 ± 3.69	-3.43 ± 4.01	2.29 ± 5.48	2.52 ± 1.63
Object 2						
Sub 2	7.28 ± 4.35	5.36 ± 6.42	-7.59 ± 1.33	-1.12 ± 4.35	2.61 ± 2.27	3.34 ± 0.59
Sub 3	-3.77 ± 5.26	-5.17 ± 3.85	0.65 ± 2.22	1.99 ± 3.36	-2.87± 2.72	0.94 ± 1.12
Object 3						
Sub 2	2.41 ± 2.87	0.93 ± 3.78	-4.18 ± 5.60	-0.76 ± 2.72	0.17 ± 0.48	1.89 ± 2.57
Sub 3	-5.14 ± 7.95	-6.17 ± 3.72	2.88 ± 3.14	3.27 ± 4.89	-2.68 ± 1.39	-0.21 ± 1.01

Mean and standard deviation obtained on all repetitions are reported.

In Table I, the NMES controller performance obtained by averaging all repetitions of both subjects in the four interaction tasks are reported. In terms of angles, a mean error of 5° was achieved in all sub-actions of the interactions with objects, while a higher error was found for the two sub-actions of the movement to reach the shoulder (13°). In terms of 3D-coordinates, a mean error of 2 cm was obtained in the interactions with objects, while a higher error (13 cm) was computed in the movement to touch the shoulder.

V. DISCUSSION AND CONCLUSION

The present work deals with the development of a biomimetic feedforward NMES controller integrated with a passive exoskeleton for upper limb support during daily life activities. The controller is based on TDANN and reproduces the non-linear and dynamic relationship between the kinematics and the stereotyped muscular strategy used by healthy subjects to perform the target movements.

In the definition of the stereotyped muscular strategy only the muscles that are easy and safe to be stimulated were measured and analysed: thus, we did not consider the pectoralis major even if it is recognized as one of the most important muscles in reaching movements [7].

In the planar movements performed with the support of the exoskeleton, the muscle activation was too low to recognize a reliable stereotyped strategy. To overcome this problem an additional planar resistance should be added to make the muscles work harder and exhibit larger EMG during the training session. In this study the biomimetic controller was not used to support planar movements. The biomimetic NMES controller, although it was only a feedforward controller, showed good accuracy in reaching the target points in all the anti-gravity movements (e.g. reaching the mouth from the table) and in the movements in which a smooth decrease of stimulation was needed (e.g, from the mouth to the table). Naturally, the integration of a feedback controller is foreseen to ensure the task accomplishment and to compensate for unpredictable conditions such as muscular fatigue and it will be included before testing the system on patients.

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