Intention-based EMG Control for Powered Exoskeletons

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***Abstract*—Electromyographical (EMG) signals have been frequently used to estimate human muscular torques. In the field of human-assistive robotics, these methods provide valuable information to provide effective support to the user. However, their usability is strongly limited by the necessity of complex user-dependent and session-dependent calibration procedures, which confine their use to the laboratory environment. Nonetheless, an accurate estimate of muscle torque could be not necessary to provide effective movement assistance to the users. The natural ability of human CNS of adapting to external disturbances could compensate for a lower accuracy of the torque provided by the robot and maintain the movement accuracy unaltered, while the effort is reduced. In order to explore this possibility, in this paper we study the reaction of 10 healthy subjects to the assistance provided through a proportional EMG control applied by an elbow powered exoskeleton. This system gives only a rough estimate of the user muscular torque but does not require any specific calibration. Experimental results clearly show that subjects adapt almost instantaneously to the assistance provided by the robot and can reduce their effort while keeping full control of the movement in different dynamic conditions (i.e. no alterations of movement accuracy are observed).**

***Index Terms*—powered exoskeletons, EMG control, assistive robotics.**

I. Introduction

POWERED exoskeletons are wearable robots designed to assist human movements. The assistance provided by these devices can be exploited to several ends: to augment the performance of healthy humans, enhancing their endurance [1]-[3] or strength [4], to restore normal abilities in patients affected by movement disorders, such as tremor [5][6], hemiplegia [7][8] or paraplegia [9][10], or finally to enhance the outcome of neuro-muscular rehabilitation [11]-[13].

Despite the very different goals a common issue arises: the design of a human-robot interface capable of understanding the intention of the user and reacting appropriately to timely provide the required assistance.

A widely investigated methodology to achieve this goal is based on the estimation of the joint torque needed to perform the movement, and the provision of a constant fraction of said torque to the wearer by means of a robot [14][15]. As a result of the assistance, users are facilitated in performing the task provided that they can adapt their motor behavior in terms of muscle activations to exploit the external assisting torque. The expected outcome is that, thanks to the robot-mediated assistance, the subject can perform the desired task with less muscle effort [16], and/or recover the normal movement ability and arm strength of a healthy subject [5].

A possible strategy for estimating the torque needed to perform a movement consists in measuring the activation of the involved muscles through electromyography (EMG). EMG signals, resulting from the motor neuron impulses that activate the muscle fibres, can be correlated with the force produced by muscles and the resulting torque at the joint level [19][20]. The relation between EMG signals and torque is however very complex. It involves several non-linearities in both static and dynamic conditions, and strongly depends on the subject anatomy and the placement of electrodes. Under controlled conditions, the final EMG-torque relationship can be modeled by a second order filter with a bandwidth of about 2-3 Hz [21][22] with good results. Accordingly, the incipit of EMG signal starts about 20-80 ms before the muscle contraction takes place [23].

The main drawback of EMG-based torque estimation methods is intrinsic in the complex subject- and session-dependent calibrations that are required to produce an accurate and reliable model. This procedure is time-consuming and cannot be done by the subject wearing the exoskeleton alone. Furthermore, it often requires supplemental technical equipment to be performed. For these reasons, all these methods can be hardly applied outside of the laboratory environment.

Compared to model-based methods (i.e. inverse dynamics models [19][20]), EMG-based techniques have the advantage of not requiring a dynamic model of the limb and of its interaction with the environment. This is appealing in a real-world scenario, when solving inverse dynamic equations and measuring interaction forces could be impracticable.

Different algorithmical approaches have been proposed in the past to estimate the muscular torques starting from EMG activation, ranging from black-box neural networks [24], neuro-fuzzy classifiers [25], and Hill models [26][27]. Particular attention was given to reduce the complexity of the calibration procedures, lowering, at the same time, the required computational power [28]. More recently, combined

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force-position estimates from EMG have been proposed as a method to teleoperate robotic arms and control exoskeletons [29][30].

Most efforts, however, have been spent to increase the accuracy of these methods, which is definitely important in biomechanics and physiology, but could be possibly unnecessary for providing effective robotic assistance by means of an exoskeleton. Moreover, the need for using powered exoskeletons in a home environment requires to find simplified solutions for the human-robot interface that could combine ease of use and effectiveness in assisting the wearer movement. Independently of the specific goal of the robot-mediated assistance (e.g. improve the living independence of elderly persons, increase the autonomy of disabled people) the use of a wearable robot in daily living should not require the need for an external person to be worn, tuned or used.

With a view to the achievement of this long term objective, in this paper we focus on the analysis of the closed-loop usability of a simplified EMG-based assistive robotic system. The proposed human-robot interface uses EMG signals to continuously detect the users' movement intention (in terms of direction and intensity of the muscle effort) and to assist the movement execution through a powered exoskeleton. The basic idea is to provide users with a torque proportional to their muscle-activation intensity, so that each muscle is artificially strengthened by the action of the exoskeleton.

Specifically, we applied an assistive torque proportional to the envelope of the EMGs from the main muscles involved in the movement and coherent with their action (i.e. agonist-antagonist role). As already shown in [31] even with a through calibration, EMG envelopes can provide only a rough estimate of the torque exerted during the movement. Nevertheless, it can nicely approximate the muscle activation level and the direction of the intended movement (e.g. flexion vs. extension).

We hypothesize that, by giving a robot assistance *coherent* with the intended movement, the CNS ability to adapt and exploit external motor disturbances will allow the person to compensate for the torque estimate imprecision, and still benefit (in terms of reduced muscular effort) from the robot assistance while keeping full control of the movement. In addition, in order to simulate a plausible real-world situation we avoid any kind of calibration of the system, and leave the freedom of choosing the gain between EMG envelope and robot-provided torque to the subjects.

To test the proposed controller, we setup a demanding elbow flexion-extension task, with a pace and amplitude imposed by the experimenter through a metronome and a visual feedback. It is our interest not only to reduce the effort of the users (i.e. their muscle activations) but also to verify that the normal movement accuracy is maintained.

Our results support this hypothesis by showing that subjects can adapt almost instantaneously to the assistance provided by the exoskeleton by reducing their muscle effort while maintaining the joint trajectory unaltered.

This paper presents the description of the EMG-based proportional control system along with its implementation on the NEUROExos platform, a powered exoskeleton for the elbow assistance. The proposed assistive control was tested on ten healthy subjects performing an elbow flexion/extension movement against gravity (i.e. in non-isometric, non-isotonic muscle contraction conditions). Results of the experiments along with discussion are reported. Preliminary results were submitted to a conference [32].

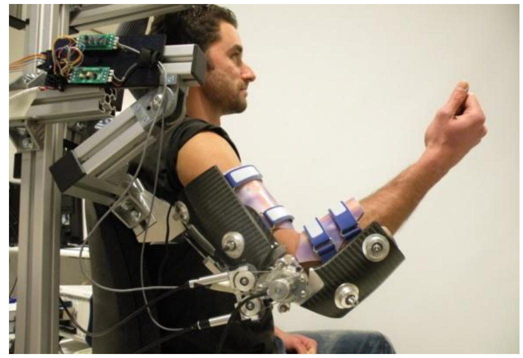

Fig. 1 Overview of a subject wearing the NEUROExos elbow exoskeleton during experimental session

II. Methods

A. The NEUROExos platform

Assistance to the elbow joint was provided through the elbow powered exoskeleton NEUROExos, (see [33][34] for an extensive description) – shown in Fig. 1 – designed to provide high fidelity torque to the user joint.

User's upper- and lower-arm were rigidly connected to the robot through orthotic shells, designed to improve comfort and to minimize peak pressures on the skin [35][36]. NEUROExos is powered by two remote antagonist actuators (i.e. a flexor and an extensor) mimicking the function and configuration of human muscles [37][38]. The platform is equipped with a 4096 ppr rotary encoder and with two cable force sensors. Each antagonist actuator is controlled by an independent closed-loop force control having a bandwidth of 11 Hz. The force controllers can be synchronized to achieve the desired torque at the joint level. The lower-arm link of NEUROExos has inertia of only 0.007 Kgm^2. The mechanical impedance in zero-torque control is about 2Nm/rad, ensuring a good transparency of the robot.

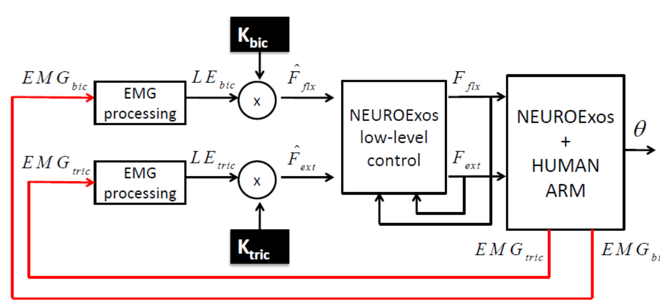

Fig. 2 Block diagram of the proportional EMG controller.

B. EMG Processing and proportional controller

Surface EMG activity from the biceps brachii and triceps brachii (long head) muscle were picked up by pre-gelled Ag/AgCl 8 mm diameter bipolar surface electrodes (Pirronse&Co., Italy) attached 2 cm apart along the longitudinal axis of the muscle belly. EMG recordings were digitized at 1 kHz using the Telemyo 2400R G2 analog output receiver (Noraxon USA Inc., AZ, USA) with an internal band-pass filter (10-500 Hz) and a gain coefficient of 2000. Raw EMG signals were processed to obtain the linear envelope (LE) profiles, which are known to resemble the muscle tension waveforms during dynamic changes of isometric forces [39]. LEs were obtained on-line through full-wave rectification of band-passed EMG signals and post-filtering by means of a second-order low-pass Butterworth filter with a 3 Hz cut-off frequency [40]. This value has been chosen by considering previous studies about muscle contraction dynamics [19] and pilot trials on our platform.

As showed in the NEUROExos control scheme (see Fig. 2), LEs recorded from biceps and triceps (i.e. LE_{bic} and LE_{tric}) were multiplied by two different constant factors K_{bic} and K_{tric}, to obtain the force set-points for the NEUROExos flexor and extensor actuator respectively ($\hat{F}_{flx}$ and $\hat{F}_{ext}$). Cable forces (F_{flx} and F_{ext}) were regulated by the NEUROExos closed-loop low-level controller to produce the final assistive torque on the user joint. EMG recordings, together with kinematic and force data from the exoskeleton were synchronized and saved by means of a Labview® routine running at 1 kHz on a real-time controller NI PXI-8196 (National Instrument, TX, USA).

C. Experimental Procedures

Ten healthy right-handed volunteer subjects took part to the experiment (age 23-34, four female, six male). No subject had previously experienced EMG control on the exoskeleton. All participants signed an informed consent before the experiment took place.

Subjects sat on a chair and wore the NEUROExos on their right arm. The weight of NEUROExos was supported by an external frame, which also constrained the upper arm to an inclination of about 30 deg with respect to the gravity vector, as shown in Fig. 1.

Before starting the experimental procedure, the subject chose the two preferred gains of the proportional controllers (K_{bic} and K_{tric}), one after the other, starting from the biceps. Both gain values were initially set to 0. The subject was instructed to increase the gain gradually using a knob while moving his/her right elbow freely. The experimenter exhorted the subjects to increase the gain as long as they felt comfortable with the level of assistance. No time constraint was given for this operation, but in no case more than 2 minutes were needed. After the preferred gain values were chosen, subjects took rest for 5 minutes outside the exoskeleton before starting the experimental procedure.

During the experiment, participants were asked to make cyclical flexion/extension movements with a target amplitude and pace supplied by the computer. Augmented visual feedback was provided to subjects using a computer screen, showing current elbow angle through a vertical cursor and target movement range with upper and lower limits. In addition, a metronome supplied the desired movement pace to which the user was asked to synchronize. The goal was to execute a full cycle of the required movement within two consecutive beeps. The exoskeleton did not react in any way to errors in movement pace or amplitude performed by the user. Therefore subjects were in full control of the movement, and experienced no constraints.

The experiment included three different trials that tested the adaptation of the subjects to the proposed controller under different movement conditions and increasing levels of assistance. The protocol of each trial is hereafter reported:

Trial 1) *Hand-free movement at a constant pace*.
Participants were asked to perform flexion/extension movement with a target pace of 1Hz. While performing this cyclical movement, subjects experienced three increasing level of assistance obtained by setting the force gain values (K_{bic} and K_{tric}) to 50%, 100% and 150% of the preferred values previously chosen (see panel A of Fig. 3). Each level of assistance was maintained for one minute, and was interleaved by 1 minute of no-assistance condition (K_{bic} and K_{tric} equal to 0) in order to wash out potential adaptation effects. Trial 1 therefore consisted of seven one-minute sequences, resulting in seven minutes of continuous cyclical movement.

Trial 2) *Weight-lifting at constant pace*.
Participants repeated the protocol of the first trial while holding a 1 Kg weight dumbbell with their right hand for the whole duration of the trial.

Trial 3) *Hand-free movement at variable pace*.
Participants were asked to execute a cyclical flexion/extension movement at a constant pace. Every 60 seconds the movement target pace was changed according to the following sequence: 1Hz, 0.75Hz, 1Hz, 1.25Hz, 1Hz (see panel A of Fig. 5). This procedure was performed two times at different assistance level, interleaved by two minutes of rest. During the first session, K_{bic} and K_{tric} were equal to 100% the preferred values; in the second, K_{bic} and K_{tric} were set to 0 (i.e., no assistance) to obtain the reference performance of the subject.

In all trials, reference amplitude and offset were kept constant at 25° (i.e. total elbow excursion equals to 50°) and 70° respectively. Subjects performed the three trials one after another, interleaved by 10-minutes resting periods outside the exoskeleton. Each trial was iterated two times to verify the familiarization of subject to the proposed controller and to assess longer term adaptation [41].

D. Data Analysis

In order to analyze the movement kinematics the angular position was filtered (first order Butterworth with 25Hz cut-off frequency) and differentiated twice to get the angular velocity and acceleration. These variables, together with all the raw data acquired during the experiment (i.e. joint angle, EMGs, LEs, Forces, Torque) were divided into sequences of 60 seconds with (1) homogeneous levels of assistance (50%, 100% and 150%) and (2) constant target pace. Each of these

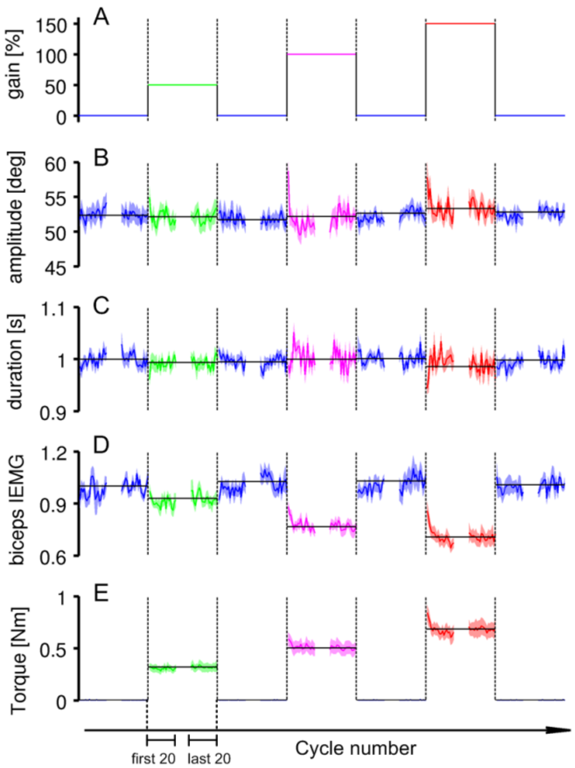

Fig. 4 Kinematic and dynamic variables averaged across all subjects and repetitions for Trial 1 (free movement). Data is shown for the first and last 20 cycles for each condition (solid line), along with the standard error contour (shadowed) and the mean value (black line). From top to bottom: relative gain value (A), cycle amplitude (B), cycle duration (C), normalized biceps integral (D), average torque (E).

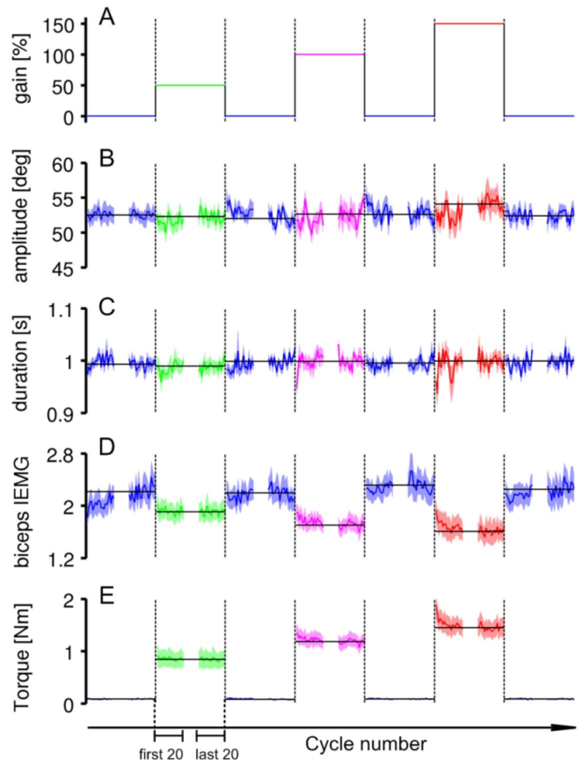

Fig. 3 Kinematic and dynamic variables averaged across all subjects and repetitions for Trial 2 (weight-lifting movement). Data is shown for the first and last 20 cycles for each condition (solid line), along with the standard error contour (shadowed) and the mean value (black line). From top to bottom: relative gain value (A), cycle amplitude (B), cycle duration (C), normalized biceps integral (D), average torque (E).

sequences was separated in individual cycles using a peak detection algorithm on the angular position signal. Cycles during which a transition occurred were not included in the analysis. Within each cycle, we computed cycle amplitude (difference between the maximum and the minimum), cycle duration and EMGs integral (IEMG). Finally, IEMGs were normalized for each subject and each muscle separately, by using the average IEMG computed on the cycles of the 1 Hz sequences in no-assistance condition. This allows comparing IEMGs of different subjects.

Given that a non-constant number of full-movement cycles were performed within each 60-seconds sequence, we kept the data corresponding to the first and last 20 cycles for the analysis of the transitory and stationary behavior respectively. In the followings, statistics were calculated on stationary behavior only.

Preliminary statistical tests (N-way repeated measures ANOVA) revealed that the effect of the iteration (i.e. the repetition of identical trials by the same subject) was not significant for all the above mentioned dependent variables (i.e. cycle amplitude and duration, IEMG). Both the main-effect and the interaction with the other factors never reached significance (all p's >0.32). For this reason, the two iterations of the same trial were pooled together in the subsequent statistical tests and figures.

Trial 1 and Trial 2 were analyzed using two-way repeated measures ANOVA (mixed design) with subject ID as between-subject factor and assistance level as within-subject factor. On the other hand, three-way repeated measures ANOVA (mixed design) was used to examine the results of trial 3, by using subject ID as between-subject factor, level of assistance and target movement pace as within-subject factors. When required, post-hoc comparison were tested by means of Tukey HSD method and displayed through confidence intervals.

The reason of using subject ID as a factor is that subjects chose the preferred gain values autonomously, leading to a subject-dependent level of assistance. As a consequence, it was of interest to test the effect of that choice on the kinematic performances and on the muscular activations (i.e., the dependent variables of the analysis).

All data processing was performed by using Matlab (The MathWorks, Natick, MA, USA). Statistics tests were computed via SPSS (IBM SPSS, Somer, NY, USA) by setting the significance level at an alpha value of 0.05.

III. Results

A. *Kinematic performance*

The analysis of the kinematic performance was aimed at investigating how subjects adapted to the extra-torque provided by the robot. Specifically it aimed to test if subjects could fulfill the required rhythmic tasks despite the simplified assistive controller experienced in the three trials.

As mentioned earlier, we extracted the amplitude and duration of each cycle. The average of these variables across all the subjects along with standard errors are shown in panel B and C of Fig 3, Fig. 4 and Fig. 5, which report the results of trial 1, 2 and 3 respectively. These figures show two important results. First, by looking at the stationary phases (last 20 cycles of each sequence) it is clear that subjects could fulfill the required motor tasks (in terms of movement range and pace) no matter the level of assistance provided, the extra-weight to be lifted, or the difference in target movement pace.

On the other hand, visual inspection of the transitory phases (first 20 cycles of each sequence in Fig. 3 and Fig. 4) highlighted that subjects adapted almost instantaneously to changes in the assistance level. The movement amplitude increased for one cycle after the gain change, but was quickly recovered within 3 to 5 cycles. Similarly, the cycle duration decreased on the first cycle after the transition occurred, then it returned to its stationary level within 3 to 5 cycles. Also, results from trial 3 demonstrated that subjects could adjust the movement pace almost instantaneously, even when the assistance was active. Subjects showed to adapt to the new pace by modifying the cycle duration within 3 to 5 cycles after the transition occurred, as shown in panel C of Fig. 5, after the vertical dotted vertical line. Notably, no difference in

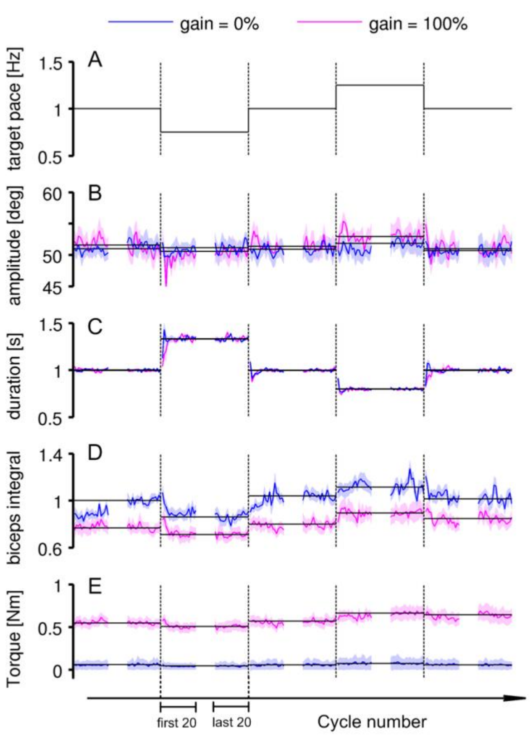

Fig. 5 Kinematic and dynamic variables averaged across all subjects and repetitions for Trial 3. Data is shown for the first and last 20 cycles for each condition (solid line), along with the standard error contour (shadowed) and the mean value (black line). Results obtained using different gains are reported in different colors. From top to bottom: target movement pace (A), cycle amplitude (B), cycle duration (C), normalized biceps integral (D), and average torque (E).

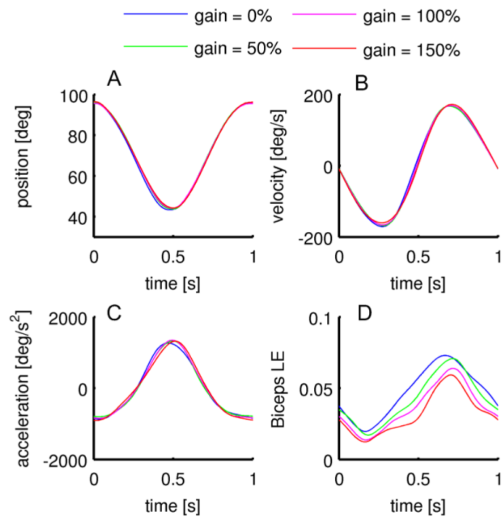

Fig. 6 Steady-state profiles of position (A), velocity (B), acceleration (C) and biceps linear envelope (D) for one representative subject. These profiles were obtained by resampling the actual trajectories over 1000 equally spaced samples for each cycle, then averaging on the steady-state cycles of each gain separately.

adaptation to the new pace was evident between no-assistance and the assisted condition (i.e. differences between blue and magenta lines are indeed hardly visible in panel C of Fig. 5) Mean position, velocity and acceleration profiles in stationary state were also calculated for each assistance level, and are reported in Fig. 6 (panel A, B and C) with different colors, for a single representative subject. It can be seen that the movement kinematics was not altered by the assistance provided by the exoskeleton.

ANOVA on the stationary performance for all the three trials revealed that the movement duration was not affected by any of the tested factor (see Table I and Fig. 7). All p's are indeed greater than 0.74. On the contrary, significant differences existed in the movement range if subject-ID factor is considered ($p<10^{-6}$), meaning that subjects tended to perform slightly different movement ranges, even though these differences were very small (about 2°). Importantly, the movement amplitude was not affected by the gain-level factor in any trial (all p's >0.059) as can be seen by the confidence interval reported on Fig. 7. This result confirms that the proposed assistive controller did not modify the ability of the subjects to control the high level features of the movement (e.g. pace, amplitude).

B. *Effort reduction*

To prove the effectiveness of the proposed assistive strategy in lowering the effort spent by the wearer, we computed the EMG integral (IEMG), which is recognized to be one of the best measures of the total muscular effort. [42]. Being the elbow movement performed against gravity, triceps muscle was not significantly activated during the trials. (i.e. the max activation of the triceps within a movement cycle was always under three times the standard deviation of the corresponding EMG signal at rest) As a consequence the results in the followings are reported for biceps only.

The visual inspection of IEMG on trial 1 (see panel D of

Fig. 3) outlines that the muscular effort at the stationary state was strongly dependent on the level of assistance provided by the robot. Specifically, when K was set to 50%, 100% and 150% of the subject-preferred value, we observed a IEMG reduction of 13.02%, 23.14%, 31.34% respectively (see Fig. 7), compared to the no-assistance condition (K = 0). Coherently, the mean torque over the cycle increased with the level of assistance, indicating that an extra flexion torque is provided during the trial (see panel E of Fig. 3 and panel A of Fig. 7).

As shown in panel D of Fig. 4, analogous results were obtained in trial 2, when subjects lifted a 1 Kg dumb-bell. In that case, we recorded a reduction on the IEMG of 10.5%, 20.65% and 28.47% (compared to the no-assistance condition with extra-weight) for the same three increasing proportional gains (50%, 100% and 150% of the preferred value). Despite the similar percentage IEMG reduction between trial 1 and trial 2, the comparison among panel D of Fig 3 and Fig 4 revealed that the effort was approximately doubled in trial 2 because of the additional weight. As a consequence, the joint torque increased as well (see panel E, Fig.3 and Fig.4)

Focusing on the transient phases of both trial 1 and trial 2 (first 20 cycles of each sequence panel D, Fig. 3 and Fig. 4), it is clear that subjects adapted their muscle activations very fast to compensate for the extra-torque provided by the robot. In agreement with the cycle amplitude, the IEMG decreased rapidly after the gain shift, and achieved its stationary level within 3 to 5 movement cycles.

The mean profiles of the biceps envelope were also calculated for each assistance level and are represented with different colors in panel D of Fig 6, for a single representative subject. It can be seen that the assistive controller did not alter significantly the shape of the LE profiles along the movement cycle, while it reduced considerably the effort of the user. Higher proportional gains led to lower LE profiles.

The ANOVA analysis on the stationary state established the statistical significance of the main effect of the gain level factor on both biceps IEMG and joint torque for trial 1 and trial 2 (all p's $< 10^{-6}$, see Table 1). Post-hoc tests (Tukey HSD) in the IEMG revealed a significant difference between all the different assistance conditions (i.e. gain levels) that we tested (see Fig. 7 for the pairwise comparison of ANOVA results). In addition, a significant interaction was present between the subject ID and the gain-level (all p's$<10^{-6}$), pointing out that not only each participant tended to choose a different level of assistance by setting the preferred K values, but also that this choice affected the capability of adapting to the assistance and then to save effort.

Similar analysis was performed on the results of trial 3. The cycle by cycle evolution of biceps IEMG and joint torque during this trial are reported in panel D and E of Fig 5; where the results for the no-assistance condition are superimposed to the one obtained at the preferred assistance level. Again, the most evident effect of the assistance controller is a marked decrease in the IEMG that is observed for any tested movement pace, as reported on the different sequences in Fig. 5. Not surprisingly, the movement pace affected proportionally the IEMG: the higher the pace the higher the effort. The ANOVA analysis pointed out the statistical significance of the observed difference in IEMG and joint torque for both the main effect of assistance level, target pace and subject-ID factors (all p's $< 10^{-6}$). Post-hoc tests (Tukey

Table I
ANOVA results for trials 1, 2 and 3. In red are highlighted the statistically significant results.

	Amplitude [°]		Duration [s]		IEMG		Torque [Nm]	
Trial 1								
Subject ID	F(9,190) = 56.732	$p<10^{-6}$	F(9,190) = 0.654	$p = 0.7496$	F(9,190) = 18.906	$p<10^{-6}$	F(9,190) = 451.714	$p<10^{-6}$
Gain level	F(3,570) = 2.5354	$p = 0.0559$	F(3,570) = 1.481	$p = 0.2186$	F(3,570) = 631.288	$p<10^{-6}$	F(3,570) = 7343.25	$p<10^{-6}$
Subject ID * Gain level	F(27,570) = 1.233	$p = 0.1951$	F(27,570) = 1.310	$p = 0.1373$	F(27,570) =11.690	$p<10^{-6}$	F(27,570) =66.364	$p<10^{-6}$
Trial 2								
Subject ID	F(9,190) = 61.975	$p<10^{-6}$	F(9,190) = 0.926	$p = 0.5036$	F(9,190) = 18.906	$p<10^{-6}$	F(9,190) = 18.906	$p<10^{-6}$
Gain level	F(3,570) = 2.381	$p = 0.0686$	F(3,570) = 2.432	$p = 0.0641$	F(3,570) = 631.288	$p<10^{-6}$	F(3,570) = 631.288	$p<10^{-6}$
Subject ID * Gain level	F(27,570) =1.124	$p = 0.3047$	F(27,570) =1.055	$p = 0.3905$	F(27,570) =1.310	$p<10^{-6}$	F(27,570) =11.690	$p<10^{-6}$
Trial 3								
Subject ID	F(9,190) = 236.73	$p<10^{-6}$	F(9,190) = 0.473	$p = 0.8914$	F(9,190) = 105.867	$p<10^{-6}$	F(9,190) = 709.683	$p<10^{-6}$
Gain level	F(1,190) = 3.575	$p = 0.061$	F(1,190) = 1.124	$p = 0.2904$	F(1,190) = 1006.390	$p<10^{-6}$	F(1,190) = 29105.7	$p<10^{-6}$
Target frequency	F(2,380) = 2.344	$p =0.0973$	F(2,380) = 11841.753	$p<10^{-4}$	F(2,380) = 424.751	$p<10^{-6}$	F(2,380) = 332.087	$p<10^{-6}$
Subject ID * Gain level	F(9,190) = 1.356	$p = 0.2108$	F(9,190) = 0.203	$p = 0.9936$	F(9,190) = 47.536	$p<10^{-5}$	F(9,190) = 811.389	$p<10^{-6}$
Gain level * Target frequency	F(2,380) = 0.963	$p = 0.3826$	F(2,380) = 0.094	$p = 0.9103$	F(2,380) = 10.073	$p<10^{-3}$	F(2,380) = 162.900	$p<10^{-6}$

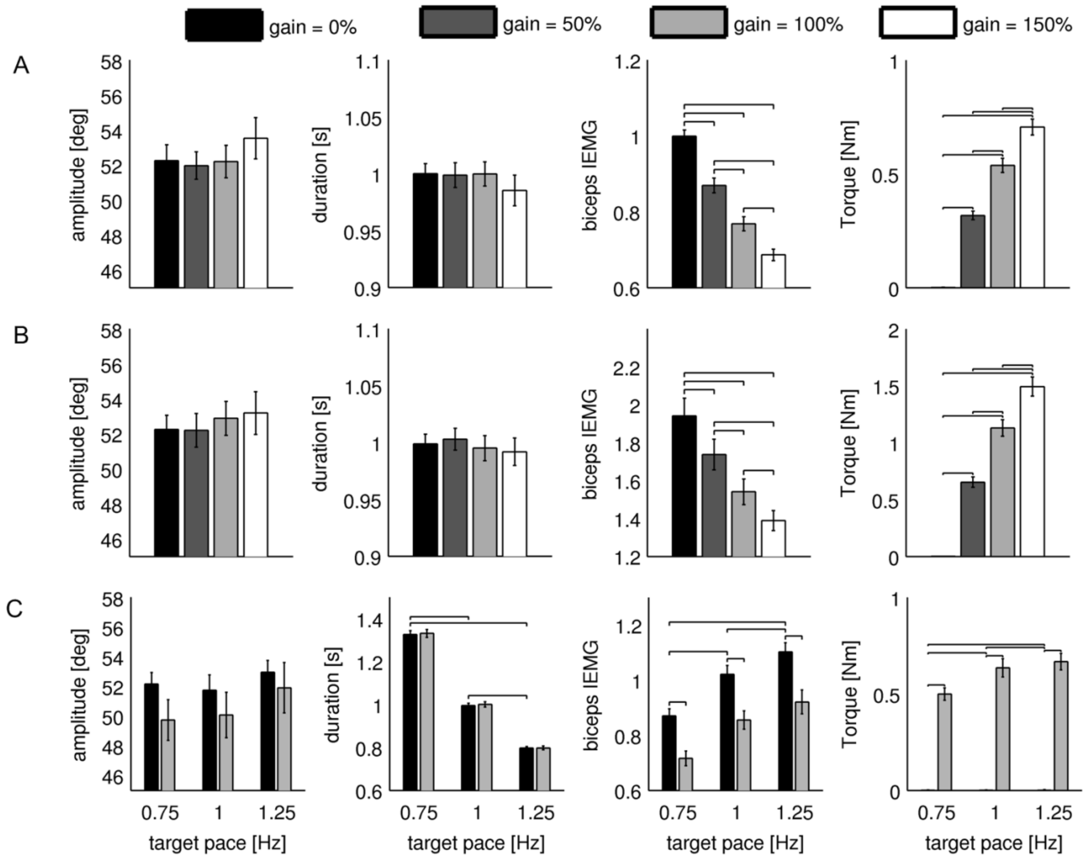

Fig. 5 Steady-state kinematic and dynamic variables averaged for each tested gain separately across all subjects and repetitions for Trial 1 (A), Trial 2 (B), trial 3 (C). Each bar represents values obtained by averaging the over the 20 steady-state cycles. Error bars indicate the 99% confidence interval of each variable. Horizontal braces indicate a statistically significant difference obtained through ANOVA.

HSD) in the IEMG and mean torque revealed a significant difference between the two assistance conditions (i.e. gain levels) and the three frequencies that we tested (see Fig. 7). Again, the interaction between gain-level and subject-ID was significant ($p<10^{-5}$). Significance was also reached by the interaction between gain-level and target frequency ($p< 10^{-3}$).

IV. Discussion

A. Evidences from the experimental results

The experimental results shown in the last section clearly demonstrate that subjects could keep the full control of their arm movement during the action of the EMG-proportional assistive controller. Movement kinematics was not significantly altered in any tested condition. With the EMG assistance on, participants successfully performed the rhythmic task also in the presence of an additional weight (Fig 5), with no need of changing the gains. Moreover, subjects could change the movement pace as required by the experimental protocol of task 3 (Fig. 6).

In all tested conditions participants could reduce the effort spent to move the arm, as shown by the considerable biceps IEMGs drop off. This result is remarkable if we consider the well-known difficulties of EMG-based control in assisting movements that require very low muscular effort [25], and consequently produce low EMG signals, such as the unconstrained elbow movement that we tested in trial 1.

Motor adaptation to novel dynamical environments has been widely investigated in the past by applying force/torque to the subjects' upper and lower limbs through pre-programmed robots (see e.g. [43]-[45]). This study provides further experimental results on this topic, with a disturbance modulated by users themselves through muscular activations, rather than being pre-programmed [46] or dependent on the movement kinematics [47]. Because of the EMG proportional control, the re-modulation of the muscles' activation had a twofold effect. On one side it showed that users adapted (i.e. reduced) the muscular torque to preserve the intended movement in the presence of the power amplification. On the other side, it reduced the source of the disturbance itself because it lowered the muscles' LE and then the extra-torque given by of the robot.

From a motor adaptation perspective, feedback is also very important [48]. In our experiment, beyond the augmented visual feedback, users could rely on the strong haptic response generated by the physical interaction with the exoskeleton. The skin mechanoreceptors could indeed perceive the action of the robot as an increased pressure on the arm, before the actual movement started [49].

In this study we found a very fast adaptation of subjects to the disturbances induced by the EMG controller, as shown by the analysis of the cycle-by-cycle evolution of the recorded variables (see Fig 3, Fig. 4 and Fig. 5). All participants could recover the target movement pace and amplitude within 3 cycles after an abrupt assistance activation, regardless of the specific movement condition experienced during the trials. Coherently, the IEMG recordings reached a stationary level within the same number of cycles.

This result is in partial disagreement with the one observed by Ferris [16][50], who applied a similar EMG proportional control to a powered ankle-foot orthosis and observed a very slow adaptation of subjects to the action of the robot (i.e., in the order of minutes). Certainly, part of this divergence can be attributed to the differences in the neural mechanisms underlying the movement generation of lower and upper limb. Nonetheless, we believe a crucial role was played by the augmented feedback we provided to participants through visual stimuli that was not present in the setup of Ferris and colleagues. This augmented feedback could have been fundamental for the subjects to build an internal dynamic model of the assistance provided by the exoskeleton and then to quickly learn how to control it. This would be in agreement with results of several studies [51][52], which showed that the visual feedback could improve the adaptation speed of healthy subjects with respect to haptic alone. Clearly this claim cannot be proven without further experiments comparing the performance achieved with and without the visual feedback.

In a previous experiment authors used the same experimental apparatus to provide movement assistance during flexion-extension movement at the elbow by using an inverse dynamic approach to estimate the movement torque and provide assistance [15]. The assistive torque provided by the robot was a constant fraction of the estimated muscular torque.

By comparing the results of the two experiments a faster adaptation to the proportional EMG control emerged (2-3 cycles are need to recover the normal performance after the assistance activation in EMG-based control, while 5-10 cycles were required for the inverse dynamic based approach) despite the lower accuracy of the EMG-based assistive torque. We supposed that this behavior can be attributed to a sort of "error enhancing strategy" [53] that is embedded in the proportional EMG approach. In fact, the action of the controller amplifies the effect of a given muscular activation on the performed movement. This forces the subject to converge faster to the correct movement.

A peculiarity of our experiment is that participants chose the preferred level of assistance autonomously, with the experimenter only exhorting them to have it increased until they felt comfortable. As revealed by the statistical significance of the main effect of subject ID factor on the average cycle torque (all p's $< 10^{-6}$, see Table I), each subject received a different assistive torque over the cycles. As a result, the normalized effort reduction differed among subjects (the main effect of subject ID on IEMG was statistically significant for the all the trials). Importantly, all subjects chose a gain that was sufficient to effectively reduce the movement effort. This confirms the high acceptability of the proposed controller. If this was not the case, subjects could have chosen a low gain value so as to minimize the effect of the exoskeleton assistance.

It is also of interest to note that subjects could successfully manage higher gains then the preferred ones. When the gain was set to 150% subjects could still fulfill the task and further reduce their IEMGs. Even if we did not assess the cognitive effort of participants through ad-hoc tests, all subject completed the sequence at 150% of the preferred gain without raising concerns about comfort or task difficulty. Probably, the fact that we increased progressively the assistance level during the task (see Fig. 3 and Fig. 4) helped the subject to familiarize with the assistance control and then to successfully manage higher gains than the preferred one.

At the same time we did not find any statistically relevant difference between the first and the second iteration of any trial, meaning that by repeating the same task after about half an hour did not improve the performance. This result suggests that there was not long term adaptation of subjects to the proposed controller in any tested condition.

B. Generalization of the results

The proposed approach has been tested in a restricted scenario: single joint flexion-extension task. Clearly, this is a narrow set of the possible movements performed in daily-living and the extension to other conditions has to be proven.

Nevertheless we believe that some key results emerging from this experiment can be generalized to any robot mediated assistance. The most relevant finding is that in order to assist the movement, it is not necessary to provide a constant fraction of the muscular torque. Users can adapt easily to the variable level of assistance (variable as a fraction of the torque needed to perform the movement). As a consequence, an accurate estimate of the muscular torque may be unnecessary. For the same reason, the use of complex EMG to torque calibration methods, which requires user-specific and session-specific calibration, could be relaxed to find a compromise that works in home environment.

What instead emerged to be a sufficient condition for assisting user is the aforementioned *coherence*, the persistent consistency of the robotic assistance with the user movement intention in terms of direction and intensity of the action. The assistive torque provided by our simple method follows the action of the users and increases with the effort spent by them.

This is of particular relevance when moving to the real-world scenario where multiple-joint assistance is needed. Each human articulation is indeed spanned by several agonist and antagonist muscle groups to power the joint. Each muscle can act on more than one joint or can actuate more than one degree of freedom of the same joint. In this situation our approach could be applied after a careful selection of relevant muscle activations to be measured, coherently with the intended movement. On the other hand, any EMG-torque estimation algorithm would require to measure the activation of any muscle involved in the movement and calibrate the resulting system in a very wide set of possible movement condition.

C. Application fields

EMG based control has been frequently used for assistance [25]-[28] or augmentation [54]. Few cases reported about its use in rehabilitation as a therapeutic device [56]-[58]. Importantly, none of these studies explored the time of adaptation of subjects to the controller or the resulting movement accuracy, which are two fundamental requirements to be satisfied for using the assistive system in daily-life situations.

Our findings suggest that subject can adapt almost instantaneously to a simple EMG proportional control and that movement accuracy is not significantly affected by the system. Notably, these performances are reached without a real muscle torque estimate. This is another clear advantage in order to move outside laboratories. In fact it relaxes the need of complex inter- and intra- subject calibrations, which are hardly doable without specific tools and wide technical knowledge. The proposed control amplifies the movement intent of the user with the goal of reducing the effort spent in performing a desired task. The main objective of the assistance is to reduce the effort spent in a normal task rather than to give super-human ability to the user. It is our opinion that this kind of assistance can have wide applicability in a large number of daily living situations.

In the case of elderly people, for example, lifting weights that are normal for a healthy adult can be challenging and even risky. An exoskeleton could act as a supplementary muscle apparatus that covers the gap with the adult subject and gives independence to the elderly user.

Another possible field of application for this kind of assistance could be in the factory environment, where tasks are performed iteratively and the endurance could be an issue. By lowering the effort spent in each movement the number of iteration that can be performed before the onset of fatigue can be increased.

Finally, subjects affected by muscle weakness could benefit from this kind of assistance. In these subjects, neural control is intact but muscles are not strong enough to perform simple manipulation task or even to support the weight of the arm itself. The proposed system could catch the intention of the user through a small EMG increase and help the user to perform the movement.

V. Conclusions and Future Works

The main goal of the present work was to explore the closed-loop usability of a simplified assistive control that does not require estimating the muscle torque (and therefore any specific calibration) to be successfully used in robot assistance, making it appealing in a real-world scenario.

We found strong evidence that a proportional EMG control is effective in providing movement assistance, while leaving the full control of the arm to the user. Specifically, we verify that despite the simplified assistive strategy the user keep the same kinematical accuracy (in term of amplitude and timing of the movement) while save considerable effort in performing the movement. We tested the adaptation time to this kind of assistance and found that very low (few seconds). This result confirmed our hypothesis that the human adaptation ability could compensate for the poor accuracy of the proposed controller in estimating the torque produced by muscles. Also, our results suggested that there is no need to feedback a constant fraction of torque to the user. This led us to the idea that a sufficient condition for assisting user is to continuously correlate the EMG activations with the user movement intention in terms of direction and intensity of the action.

Future works will aim to exploit these findings to the case of multiple degree of freedom robot-mediated assistance and discrete movement.

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