Evaluation of a Simultaneous Myoelectric Control Strategy for a Multi-DoF Transradial Prosthesis

Cristina Piazza, Matteo Rossi, Manuel G. Catalano, Antonio Bicchi, and Levi J. Hargrove

***Abstract*—While natural movements result from fluid coordination of multiple joints, commercial upper-limb prostheses are still limited to sequential control of multiple degrees of freedom (DoFs), or constrained to move along predefined patterns. To control multiple DoFs simultaneously, a probability-weighted regression (PWR) method has been proposed and has previously shown good performance with intramuscular electromyographic (EMG) sensors. This study aims to evaluate the PWR method for the simultaneous and proportional control of multiple DoFs using surface EMG sensors and compare the performance with a classical direct control strategy. To extract the maximum number of DoFs manageable by a user, a first analysis was conducted in a virtually simulated environment with eight able-bodied and four amputee subjects. Results show that, while using surface EMG degraded the PWR performance for the 3-DoFs control, the algorithm demonstrated excellent achievements in the 2-DoFs case. Finally, the two methods were compared on a physical experiment with amputee subjects using a hand-wrist prosthesis composed of the SoftHand Pro and the RIC Wrist Flexor. Results show comparable outcomes between the two controllers but a significantly higher wrist activation time for the PWR method, suggesting this novel method as a viable direction towards a more natural control of multi-DoFs.**

***Index Terms*—Upper Limb Prosthesis, Soft Robotics, Simultaneous Control**

I. Introduction

THE loss of an upper-limb, which affects more than half a million people just in the United States [1], is a major traumatic event that can have an impact on both the social and the working life of a person. For centuries, prostheses have been used to help with such a physical loss and still today there is a lot of interest and effort in design upper limb aids. The main claim is to fully restore the lost appearance, a smooth joint coordination and functionalities, which results very challenging due to the high number of degrees of freedom involved. Indeed, the human upper limb is an integrated system and the coordinated combination of different joints, e.g. hand and wrist, plays a key function in the execution of advanced tasks, hand mobility and manipulation [2], [3], [4].

Figure 1: An amputee subject using the hand-wrist prosthesis to stack six wooden blocks in a pyramid. The prosthesis is composed of the SoftHand Pro and the RIC Wrist Flexor.

Myoelectric prostheses, the most advanced upper-limb aids available in the market to this day, are dexterous robotic devices controlled using the electromyographic (EMG) signals from the muscles in the amputated limb. These prostheses are designed trying to match the many functions of human upper-limb through sophisticate design. Myoelectric hands are capable of performing a large span of grasp shapes [5], but typically have the drawback of being difficult to control [6]. In the last decade, robotic hands research focused on a different approach, consists of a strong reduction of the system complexity in terms of actuators and sensors, and favoured by the introduction of soft robotics technologies [7]. The combination of novel design trends and the introduction of compliance in the hand architecture have led to an innovative approach on grasping and manipulation, which already showed good results [8], [9], [10]. These devices can functionally adapt to the shape of the object and exploit the environmental constraints to get advanced configurations and increase the grasping success. In subjects with transradial amputation, the lack of wrist DoFs may also have a significant effect on the quality of the grasp execution [11] and, often, force the user to introduce unnatural compensatory movements which involve arm, shoulder and trunk [12], [13]. Relatively little research is devoted to the design and control of prosthetic

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wrists [14], and the most used solution still remains the 1 DoF prono/supination passive wrist[1].

The control strategy adopted to manage the advanced level of dexterity of multi-DoFs transradial prosthesis also plays a key role in the grasping performance. A common choice adopted to control multi-DoFs devices is, for instance, to control one degree of freedom at the time with the possibility of switching between DoFs by exerting a co-contraction above a certain threshold. This approach is undesirable from the user point of view for two main reasons: first of all, the use of co-contraction to select DoF is counterintuitive and becomes even more cumbersome with the increasing of the number of DoFs to control; secondly, this approach does not allow simultaneous control of multiple DoFs. The latter aspect is investigated in several studies [15], [16] which demonstrate that operate simultaneously a hand-wrist prosthetic system could play an important role in terms of performances and naturalness of the transradial prosthesis in daily life activities. In the attempt to eliminate the need for switching when controlling multiple DoFs, various pattern recognition control methods [17], [18] or linear methods, such as linear regression and non-negative matrix factorization [19], [20], [21], have been proposed and have recently gained popularity. Some of these control methods demonstrate their effectiveness especially when combined with innovative approaches from the clinical side, as those based on Targeted Muscle Reinnervation (TMR) [22]. This surgical technique that considerably increases users' capabilities to selectively activate several muscles more naturally, and consequently to control multiple DoFs.

In this work, we explore the advantages of using a probability-weighted regression algorithm for the simultaneous and proportional control of a transradial prosthesis (Fig 1). This control method already showed promising results with intramuscular EMG (iEMG) sensors [23] and, in this study, we evaluate the feasibility of using this algorithm in combination with surface EMG (sEMG) sensors. A first evaluation of the method was conducted in a virtual environment, analyzing the real-time performance of the probability-weighted regression system, with able-bodied individuals and amputees. The results were compared with a standard direct control (DC) and with the results of [23]. Then, to obtain a more realistic evaluation, we analyze the performance obtained by the group of amputee subjects when using a transradial prosthesis. The prosthesis is composed of an active wrist, RIC Wrist Flexor [24], and a soft underactuated hand with 19 DoFs, the SoftHand Pro (SHP) [25]. The performance of the PWR and DC methods were compared with two standardized tests and several actions mimicking daily life activities. The rest of the paper is organized as follows: Section II presents the methods and the experimental protocol. Section III presents the results while Section VI discusses the insights gained from these results and the limitations of the study. Section V draws our conclusion.

II. Methods

Eight able-bodied subjects and four subjects with transradial amputation (Table I) participated in the experiment after

Subject ID	Age	Side of amputation	Time since amputatation (yrs)	Time since TMR (yrs)
TR1	30	Left	3	0.5
TR2	25	Right	7	1
TR3	51	Right	2	2
TR4	54	Right	38	Not applicable

Table I: Amputee subjects specific details.

giving informed consent. Three of the subjects with transradial amputation had previously undergone TMR surgery. For TR1, during TMR surgery the radial nerve was transferred to the motor nerve of the pronator quadratus, the medial nerve was transferred to the flexor digitorum superficialis and the ulnar nerve was transferred to the flexor carpi ulnaris. TMR surgery for the other two subjects was performed as a clinical treatment to reduce pain associated with neuroma formation and information about nerves/muscles sites were not available. The study was approved by the Northwestern University Institutional Review Board. A first virtual experiment was conducted to evaluate the feasibility to control multi-DoFs using a PWR algorithm and sEMG. All of the subjects used sEMG to control up to 3-DoFs in a virtual Fitts' Law task (the 3DoFs corresponded to wrist pronation/supination, wrist flexion/extension and hand open/close). Then, to assess the control performance with a 2-DoFs transradial prosthesis (with active wrist flexion/extension and hand open/close), the same group of amputee subjects performed two standardized tests and tasks mimicking daily life activities. In both experiments, the order of execution was randomized between subjects to avoid favouring one through the learning effect. We point the interested reader to a short video describing the experiments.

A. Myoelectric Control

Eight pairs of electrodes were positioned around the dominant forearm of the able-bodied subjects, approximately 2 cm distal to the elbow. One pair of electrodes was placed on the main wrist flexor group, another pair was placed on the main wrist extensor group and the remaining pairs were evenly spaced on the two semicircles between these two locations. Amputee subjects were fit with a custom gel liner containing eight pairs of embedded electrodes. EMG signals were amplified using a Texas Instruments TI-ADS1299 analog front end system and sampled at 1000 Hz. To reduce noise induced by motion artifacts the signals were further filtered using a 3rd order Butterworth filter with a cut-off frequency of 20 Hz. As in [23], signals were sequenced into 250 ms windows with frame increments of 50 ms [26], [27] and ten features for each channel were extracted: four time-domain features (mean absolute value, waveform length, slope-sign changes, zero crossings) [28], along with the six coefficients of a sixth-order autoregressive model [29]. In both experimental sessions, all the computation required was done through the system embedded directly in the prosthetic socket. At the beginning of each experimental section, subjects provided a training set which was used to train a probability-weighted regression (PWR) system, following the procedure described in [23]. Two different configurations were tested: in

[1]http://www.ottobock.com/en/

the “2-DoF control” configuration, only the training data that corresponded to wrist flexion/extension, hand open/close and their combinations were used to train the algorithm, while in the “3-DoF control” all of the training data were used. Direct control (DC) was used as the baseline value for this study. With “direct control” we refer to the standard control technique in which two independent EMG signals are used to control the two directions of a single degree of freedom. In each direction of movement, the actuator is controlled proportionally to the mean absolute value (MAV) of the corresponding EMG signal. With this approach, it is only possible to control one degree of freedom at the time; switching to another DoF is possible by exerting a co-contraction above a certain threshold. Gains and thresholds were manually set at the beginning of each experimental session to exploit as much as possible the entire range of the EMG signals while minimizing erroneous movements and involuntary switching due to noise or crosstalk. Even in this case both a 2-DoF control configuration and a 3-DoF control configuration were tested.

B. *Hand-Wrist Prosthesis*

The prosthesis used for this study (Fig 1) was composed of the RIC Wrist Flexor and the SoftHand Pro (SHP). The RIC Wrist Flexor [24] is a compact and powerful wrist flexor with dimensions of 35mm x 45mm x 58mm, a mass of 142 g, and a no-load speed of 85 r/min. It can produce a stall torque of 2.5 N and it is equipped with the universal quick disconnect [30], developed by Motion Control, Inc. The SHP is the EMG controlled version of the Pisa/IIT SoftHand (SH), which is a soft robotic anthropomorphic hand with 19 joints and one motor [31]. Each finger is composed of a group of rolling joints connected by elastic ligaments; a single tendon runs through all the fingers and actuates them in a coordinated way when pulled by the motor. This design makes the SH very robust and able to stand severe joint dislocations and disarticulations. The SH is synergy inspired: when actuated it moves following the first synergy of grasp [32]. The SHP is a versatile robotic hand that can adapt its shape to the object that it is being grasped. Even if the SHP uses only one motor, its adaptive design allows a natural and safe interaction with objects and environmental constrain [33]. The current release has a maximum force of 130 N perpendicular to the palm and employs a 15 Watt Maxon DCX 22S motor with a GPX22 (86:1) gearhead and a 12-bit Austrian Microsystems magnetic encoder, with a resolution of 0:0875. The CAD model and the electronic board design of the SH are open source and available at the Natural Machine Motion Initiative [31].

C. *Virtual Experiments*

EMG control was evaluated using a Fitts’ law test in a virtual environment [23], [34]. Fig 2 shows the experimental setup. Subjects were placed in front of a computer screen with their elbow flexed at 90 degrees. The screen displayed a black and an orange ring, representing respectively the cursor and the target. Subjects controlled the position of the cursor using the aforementioned control techniques: the speed of horizontal displacement was controlled by a wrist flexion/extension signal and the speed of change of the cursor radius was controlled by a hand open/close signal; in the 3-DoF control configurations, the speed of vertical displacement was controlled by the wrist pronation/supination signal. The task consisted in moving the cursor to reach the target as quickly as possible and maintain the cursor in an overlapping position with the target for two consecutive seconds, after which the target was considered successfully acquired. Subjects were neither encouraged nor discouraged from using simultaneous control of the DoFs. The task was considered failed after 5 overshoots (i.e., when the cursor moved into and out of the target) or if the target was not acquired within 30s. Two to three levels of target complexity were presented depending on the control configuration: “1-DoF targets” required the subjects to use only one DoF, “2-DoF targets” required the use of at least two DoFs and “3-DoF targets” required the subjects to activate three DoFs and were presented only when 3-DoF control configurations were used. For each level of complexity, six combinations of target thickness (W) and distance (D), were presented with equal frequency (Table II). For these combinations, the index of difficulty (ID) was calculated as defined by [35]:

Target Distance	Target Thickness	Index of Difficulty
40	10	2.32
40	20	1.59
40	30	1.22
80	10	3.17
80	20	2.32
80	30	1.87

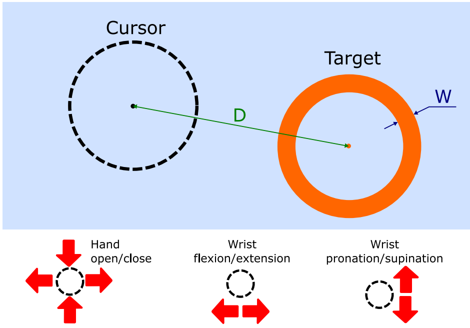
Table II: Combinations of target thickness (W) and distance (D) expressed in normalized distance units and relative index of difficulty (ID) expressed in bits.

$$ID = \log_2\left(\frac{D}{W} + 1\right). \tag{1}$$

Fitts’ law trials were presented to subjects in four experimental blocks, corresponding to the four control strategies evaluated. The blocks were presented in random order and separated by rest periods. Each combination of target complexity and index of difficulty was presented three times for the 3-DoF control configurations and five times for the 2-DoF control configurations, resulting respectively in 54 and 60 trials per block. Subjects’ performance was quantified using completion rate, throughput (TP) [36] and path efficiency (PE) [37]. The average time per target and the mean completion time in relation to the index of difficulty were also included in the analysis of the results for completeness of information. For the PWR blocks, the duration of activation of multiple DoFs during each trial was normalized over the total activation time during that trial and used to quantify subjects’ use of simultaneous control.

D. *Physical Experiments*

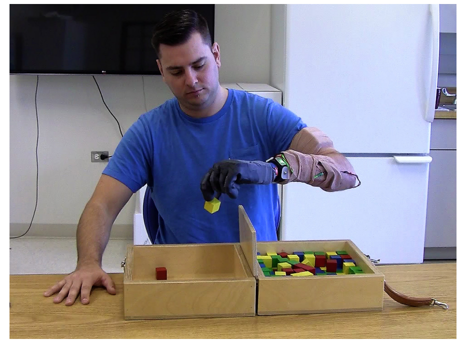
After the analysis in virtual environment described in Sec.II-C, the same group of amputee subjects took part in a physical experiment. The PWR and the DC methods were used to control a 2-DoFs device consisting of the SHP and



(a)

(b)

Figure 2: Virtual experiment. (a) A graphical representation of the target acquisition task and all of the possible movements of the cursor. The dashed circle represents the cursor, while the orange thick circle represents the target. Arrows are used to indicate target width (W) and distance from the cursor (D). (b) Subject controlling a ring-shaped cursor using PWR and DC to complete a Fitts' law test in virtual environment.



(a)

(b)

Figure 3: Physical experiment. Subject performing (a) Box and Blocks Test and (b) Cubbies Task. The tests were completed using a hand-wrist prosthesis controlled with PWR and DC.

the RIC wrist. According to previous studies (e.g. [38]) which highlights the predominance of the wrist flexion/extension movement over the other DoFs, only this movement was activated in the RIC wrist for the proposed investigation. Since all the subjects were naive to both devices, the experimental protocol was designed including an initial training phase to familiarize with the prosthesis, followed by two standardized tests and a subjective evaluation. Both algorithms were tested with each subject and in a random order. The experiment lasted a maximum of 4 hours (including the preparation phase) and was performed on a separate session from the virtual experiment. To prevent muscle fatigue, each subject had frequent breaks during the session. The experiment was conducted as follows:

1) Set-up and training of the prosthesis with one control algorithm. The training phase was considered over at the earliest of the following conditions: either after 20 minutes or when the subject affirmed to be able to control the hand and the wrist satisfyingly.
2) Box and Blocks Test (BBT), conducted as described in [39]. The subjects were asked to transfer as many wooden blocks as they could from one box to another within 60s (see Fig 3(a)). The blocks needed to be picked up one at a time and transported to the other box without dropping them. Subjects were granted 15s of training before the experiment. The number of blocks transferred in 60s was used as the main outcome measure.
3) Cubbies Task, conducted as described in [40]. The task consisted in picking up wooden blocks from a 4x3 cubicle system and place them on a table (see Fig 3(b)). A block was placed in each cubicle, and three blocks were placed along the top of the cubicle set, which was at the subject's eye level. The total time to complete the task was recorded and used as the main outcome measure.
4) Set-up and training of the prosthesis (conducted as in step 1) and using the remaining control strategy.
5) BBT, conducted as in step (2).
6) Cubbies Task, conducted as in step (3).
7) Subjective Evaluation, subjects were asked which was their preferred control modality and to complete tasks that mimicked daily life activities (e.g. opening/closing a fridge door, picking up objects from tables at various heights and drinking from a bottle) with the selected method. The subjects were free to perform the tasks in the way they considered the most efficient. Finally, free comments about the selected method were collected.

Time durations of hand activation, wrist activation and simultaneous activation (when applicable) were also measured during BBT and Cubbies Task.

E. Statistical Analysis

The normality of all the data sets was evaluated using a Kolmogorov-Smirnov Test. The data of the virtual test were found to be normally distributed. For these results, paired t-tests were conducted to evaluate differences between PWR and DC, for the 2-DoFs and the 3-DoFs control configurations. A multi-factorial ANOVA was used to evaluate the effect of control algorithm choice, population, tasks and their interference on path efficiency for the 2-DoFs and the 3-DoFs control configurations and throughput for 1-DoF, 2-DoFs and 3-DoFs target complexities. For the physical test, since data distributions were not gaussian, the Kruskal-Wallis test (a nonparametric analysis of variance) was used to evaluate the main outcome measures obtained with PWR and DC.

Statistical significance for all tests was set at $\alpha = 0.05$. Means are reported as *mean* $\pm$ *standard error*. Standard error is represented in figures with error bars.

III. Results

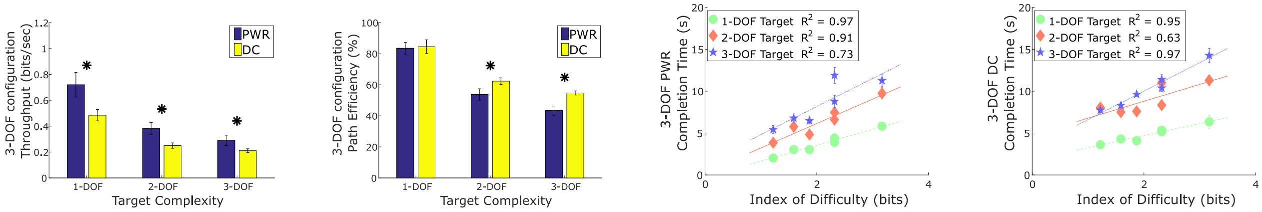
A. Virtual Experiment

1) Able-Bodied Subjects 3-DoFs Control: In the 3-DoFs control configuration, able-bodied subjects were able to successfully acquire $95.1\% \pm 1.5\%$ of targets using PWR, which was significantly lower than DC ($98.6\% \pm 0.7\%$, with p-value $p < 0.01$). For 1-DoF, 2-DoFs and 3-DoFs targets, subjects experienced significantly improved throughput when using PWR compared to DC (Fig 4(a)), with p-values $p = 0.023$, $p = 0.008$ and $p = 0.022$ respectively. These data show significant interaction effects between the control method and tasks ($p < 0.01$), but not between subjects and tasks or control methods ($p > 0.05$ for all cases). As Fig 4(b) shows, PWR resulted in significantly lower path efficiency compare to DC for 2-DoFs and 3-DoFs targets (respectively $p = 0.008$ and $p = 0.003$), while no statistically significant difference was found for 1-DoF targets. Significant interaction effects between tasks and control is present ($p < 0.01$), but no significant effects were found from the interaction with the population ($p > 0.05$ for all cases). Moreover, the average time per target obtained with PWR, $6.02s \pm 0.56$ s, was significantly lower than the average time per target obtained with DC, $7.98s \pm 0.55$ s, with a p-value $p < 0.001$. Mean completion times are plotted in Fig 4(c) and Fig 4(d); linear relationships were found between the completion times and indexes of difficulty: the R^2 values were greater than 0.90 in all cases except for 2-DoFs targets with DC ($R^2 = 0.63$) and 3-DoFs targets with PWR ($R^2 = 0.73$). Finally, average values of simultaneous activation for 1-DoF, 2-DoFs and 3-DoFs targets are reported in Table III.

2) Able-Bodied Subjects 2-DoFs Control: In the 2-DoFs control configuration, subjects successfully completed $97.5\% \pm 0.8\%$ of targets using PWR, and $99.2\% \pm 0.3\%$ of targets using DC algorithm, but this difference was not statistically significant ($p > 0.05$). Subjects experienced significantly improved throughput when using PWR compared to DC for both 1-DoF and 2-DoFs targets (Fig 5(a)), with p-values respectively of $p = 0.013$ and $p < 0.001$. Regarding path efficiency (Fig 5(b)), PWR performance was significantly worse than DC performance when comparing results for 1-DoF targets ($p = 0.0097$) but significantly better when comparing results for 2-DoFs targets ($p = 0.02$). Moreover for 2-DoF targets, the average time per target when using PWR ($3.17s \pm 0.28$ s) was significantly lower than the one obtained when using DC ($4.49s \pm 0.34$ s, with $p < 0.001$). Mean completion times varied linearly with indexes of difficulty (Fig 5(c) and Fig 5(d)), with the R^2 values for the empirical Fitt's law regression models ranging from 0.75 and 0.93. Finally, average values of simultaneous activation for 1-DoF and 2-DoFs targets are reported in Table IV.

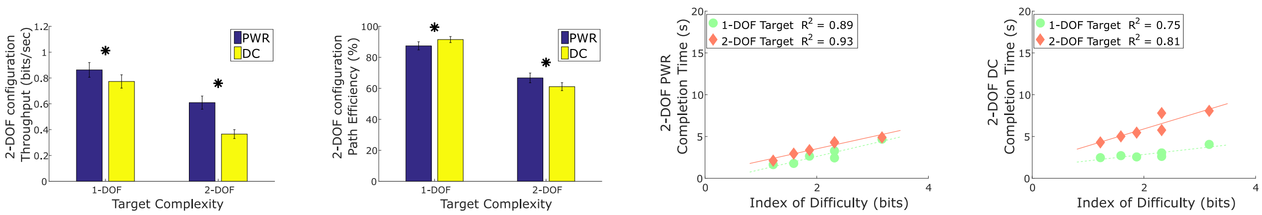
3) Amputee Subjects 3-DoFs Control: Subject TR4 experienced discomfort while performing pronation/supination movements and therefore did not complete the evaluation for the 3-DoFs control configuration; the following results are relative to TR1, TR2 and TR3 only. The completion rate obtained with PWR was $95.1\% \pm 3.3\%$ and the one obtained with DC was $93.2\% \pm 1.6\%$. This difference was not statistically significant ($p > 0.05$). The values of throughput and path efficiency are represented respectively in Fig. 6(a) and Fig 6(b); as can be seen, the differences in performance are marginal and not statistically significant ($p > 0.05$ for all cases). No significant interaction effects between tasks, subject population and control method was found ($p > 0.05$ for all cases). Moreover, the average acquisition time per target was of $8.62s \pm 1.04$ s for the PWR trials and $9.96s \pm 0.43$ s for the DC trials, but this difference was not statistically significant ($p = 0.37$). As shown in Fig 6(c) and Fig 6(d), in the majority of the considered cases, mean completion times did not vary linearly with indexes of difficulty: in two out of three cases for both PWR and DC, R^2 values for the empirical Fitt's law regression models were equal to or less than 0.54. Finally, average values of simultaneous activation for 1-DoF, 2-DoFs and 3-DoFs targets are reported in Table III.

4) Amputee Subjects 2-DoFs Control: For 2-DoF targets, the four amputee subjects completed $99.2\% \pm 0.8\%$ of targets using PWR, which was significantly higher than DC performance ($95.0\% \pm 2.0\%$ of targets, with $p < 0.01$). Fig 7(a) and Fig 7(b) show that, when comparing the performance of PWR and DC relative to 2-DoFs targets, subjects experienced significantly higher throughput ($p = 0.017$) and path efficiency ($p = 0.012$). No significant difference in terms of path efficiency or throughput was found for 1-DoF targets ($p > 0.05$). Data show no significant interaction effects between tasks, subject population and control strategy ($p > 0.05$ for all cases). Moreover, the average time per target obtained with PWR ($4.15s \pm 0.46$ s) was significantly lower than the result obtained with DC ($7.96s \pm 1.11$ s, with $p = 0.029$). Mean completion times are shown in Fig 7(c) and Fig 7(d); the R^2 values for the empirical Fitt's law regression models ranged from 0.38, in the case of 1-DoF targets with DC, to 0.91, for 1-DoF targets with PWR. Finally, average values of simultaneous activation for 1-DoF and 2-DoFs targets are reported in Table IV.



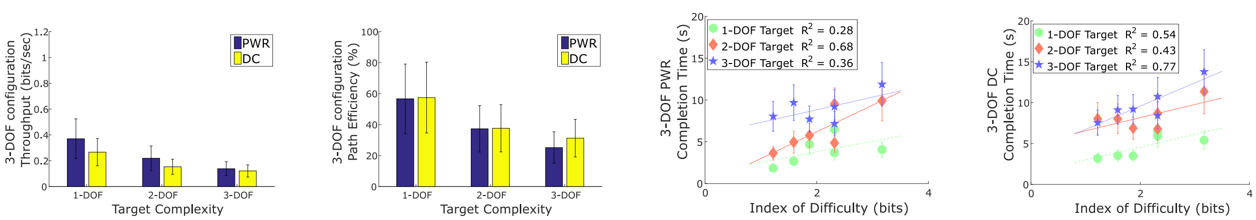
(a) (b) (c) (d)

Figure 4: Results of the virtual experiment in the 3-DoFs configuration and with able-bodied subjects: (a) compares PWR and DC throughputs for different levels of target complexity; (b) compares PWR and DC path efficiencies for different levels of target complexity; (c)-(d) present the relationship between completion time and index of difficulty respectively for PWR and DC. The R^2 values for the regression models are reported in the legend. Statistical significance ($p < 0.05$) is denoted with "*".



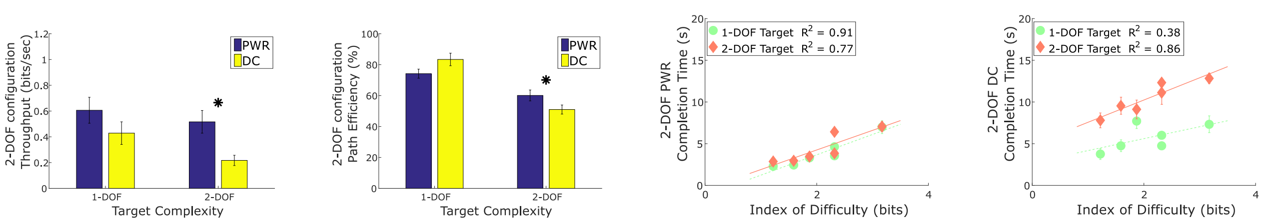
(a) (b) (c) (d)

Figure 5: Results of the virtual experiment in the 2-DoFs configuration and with able-bodied subjects: (a) compares PWR and DC throughputs for different levels of target complexity; (b) compares PWR and DC path efficiencies for different levels of target complexity; (c)-(d) present the relationship between completion time and index of difficulty respectively for PWR and DC. The R^2 values for the regression models are reported in the legend. Statistical significance ($p < 0.05$) is denoted with "*".



(a) (b) (c) (d)

Figure 6: Results of the virtual experiment in the 3-DoFs configuration and with amputee subjects: (a) compares PWR and DC throughputs for different levels of target complexity; (b) compares PWR and DC path efficiencies for different levels of target complexity; (c)-(d) present the relationship between completion time and index of difficulty respectively for PWR and DC. The R^2 values for the regression models are reported in the legend. Statistical significance ($p < 0.05$) is denoted with "*".



(a) (b) (c) (d)

Figure 7: Results of the virtual experiment in the 2-DoFs configuration and with amputee subjects: (a) compares PWR and DC throughputs for different levels of target complexity; (b) compares PWR and DC path efficiencies for different levels of target complexity; (c)-(d) present the relationship between completion time and index of difficulty respectively for PWR and DC. The R^2 values for the regression models are reported in the legend. Statistical significance ($p < 0.05$) is denoted with "*".

		2 DoFs Simultaneously	3 DoFs Simultaneously
1-DoF Targets	AB	9.7% ± 2.5%	0.9% ± 0.5%
	TR	9.4% ± 4.6%	0.4% ± 0.2%
2-DoF Targets	AB	27.4% ± 2.9%	2.1% ± 0.9%
	TR	20.6% ± 5.3%	1.3% ± 0.5%
3-DoF Targets	AB	25.8% ± 3.2%	3.1% ± 1.0%
	TR	24.6% ± 5.6%	3.5% ± 1.2%

Table III: Average percentage of simultaneous activation for 1-DoF, 2-DoF and 3-DoF targets reported both for able bodied subjects (AB) and transradial amputees (TR). The values are relative to the virtual experiment performed only with the PWR in the 3-DoF control configuration. The first column presents average percentage of time that at least 2 DoFs were simultaneously active, while the second column refer to the simultaneous activation of 3DoFs. The percentage of simultaneous activation at each trial is calculated by normalizing the duration of activation of multiple DoFs over the total activation time during that trial.

		2 DoFs Simultaneously
1-DoF Targets	AB	8.5% ± 1.2%
	TR	15.3% ± 4.4%
2-DoF Targets	AB	31.1% ± 3.2%
	TR	40.8% ± 5.3%

Table IV: Average percentage of simultaneous activation for 1-DoF and 2-DoF targets reported both for able bodied subjects (AB) and transradial amputees (TR). The values are relative to the virtual experiment performed only with the PWR in the 2-DoFs control configuration. Data refer to the average percentage of time that at least 2 DoFs were simultaneously active. The percentage of simultaneous activation at each trial is calculated by normalizing the duration of activation of multiple DoFs over the total activation time during that trial.

B. Physical Experiment

Table V presents the results of the main outcome measures for each test, control method, and the median of the group. Table VI shows the total time of hand activation, wrist activation and, in the case of PWR, a value indicating the time of simultaneous activation of hand and wrist during the test. In the BBT, the average results obtained with the PWR controller (16.25 ± 2.1) are higher compare to the DC (13.75 ± 2.5), but no statistically significant difference was found between the two control methods (p = 0.10). During this test, all of the subjects made small adjustments to the wrist position when using PWR (the average wrist activation is 2.3 sec); the wrist position was left unchanged during the entire DC trial by all the subjects. In the Cubbies Task, the average score was 108.46 ± 53.8 for the PWR controller and 120.23 ± 46.8 for the DC method. As presented in Table V, two subjects obtained better performance using PWR, while the other two performed better when using DC. No statistically significant difference was found between the two controllers (p = 0.75).

The wrist was activated more when using PWR (the average wrist activation is 10.37 sec) with respect to DC (the average wrist activation is 3.24 sec) by all of the subjects. One of the subjects managed to complete the task without activating the wrist at all during the DC trial. Simultaneous activation of hand and wrist was present in both tests. Fig 8 shows some of the tasks performed during the subjective evaluation. These tasks were chosen in order to explore the potentialities of the method while controlling a hand-wrist prosthesis during daily life activities. All of the subjects chose PWR over DC as the preferred control method, also used to complete these tasks. Finally, we collected free comments from the users:

TR1: *"PWR felt faster and more lifelike; it felt more like a natural hand and wrist"*

TR2: *"I never tried simultaneous control before but I feel that was easier to plan movements"*

TR3: *"I like the PWR but I occasionally experience unwanted co-activation of hand and wrist"*

TR4: *"I like the simultaneous control. I believe that PWR will be very functional with more and more practice"*.

	Box & Blocks Test # of blocks		**Cubbies Task total time (sec)**	
	PWR	DC	PWR	DC
TR1	15	13	74.1	115.5
TR2	18	14	184.4	166.4
TR3	18	11	108.9	141.75
TR4	14	17	66.45	57.3
Median	16.5	13.5	91.5	128.63

Table V: Results of the experiment with the prosthesis. Results include the number of blocks moved in 60s for the BBT and the time to complete the test for the Cubbies Task.

		Box & Blocks		**Cubbies**	
		PWR	DC	PWR	DC
Time per block (s)	TR1	4.00	4.62	4.94	7.70
	TR2	3.33	4.29	12.29	11.09
	TR3	3.33	5.45	7.26	9.45
	TR4	4.29	3.53	4.43	3.82
Hand activation (s)	TR1	19.30	16.57	19.06	30.99
	TR2	21.65	17.99	31.73	27.37
	TR3	24.00	13.41	31.91	15.88
	TR4	26.89	23.35	22.83	21.18
Wrist activation (s)	TR1	1.91	0.00	12.83	2.82
	TR2	5.47	0.00	18.17	6.29
	TR3	0.62	0.00	7.60	3.86
	TR4	1.21	0.00	2.87	0.00
Simultaneous activation (s)	TR1	0.63	/	2.57	/
	TR2	4.20	/	5.22	/
	TR3	0.24	/	1.95	/
	TR4	0.96	/	1.33	/

Table VI: Results of the BBT and Cubbies Task considering the average time per block, hand activation, wrist activation and simultaneous activation (for PWR) during the tests.

IV. Discussion

A probability-weighted regression (PWR) algorithm was used with sEMG sensors for the simultaneous and proportional control of multiple degrees of freedom. The algorithm, originally proposed in [23], had previously been compared to other techniques, such as linear regression, showing excellent

(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k) (l) (m) (n) (o) (p) (q) (r) (s) (t)

Figure 8: Example of activities performed using the hand-wrist prosthesis: in (a-e) and (f-j) the subjects open and close a fridge door using the wrist movements to follow the door's trajectory. (k-o) show a bimanual task that involves grasping and opening a water bottle to drink from it and closing it afterwards; wrist flexion is particularly important to ensure correct positioning of the bottle with respect to the subject's lips when drinking. (p-t) show another bimanual task in which the subject has to open a toothpaste tube and then put some toothpaste on a toothbrush.

performance both in simultaneous control of up to 3-DOFs and in isolating individual DOFs. Since the algorithm had previously been used only with iEMG sensors, in the first experiment, eight able-bodied subjects and four transradial amputees performed a Fitts' Law task in a virtual environment, to evaluate the feasibility of using the PWR algorithm with sEMG sensors. In the second experiment, the four amputee subjects used the PWR algorithm to simultaneously and proportionally control a transradial prosthesis composed by the RIC wrist flexor and the SoftHand Pro. To validate the benefits of the proposed approach, DC was used for comparison in both virtual and physical experiment. Since all of the subjects had high experience with DC, we believe that it constitutes a better benchmark with respect to other more complicated algorithm.

Two configurations of the PWR algorithm were used during the virtual experiment: in the 3-DoF control configuration the algorithm was trained to control wrist pronation/supination, wrist flexion/extension and hand open/close; in the 2-DOF control configuration, only wrist flexion/extension and hand open/close were used. In the 3-DoF control configurations, able-bodied subjects obtained significantly better throughput with PWR, but performed worse in terms of completion rate and path efficiency. In the 2-DoF control configuration, however, PWR outperformed DC in throughput and path efficiency, and the only index for which DC obtained better results was, not surprisingly, the path efficiency for 1-DoF targets. DC control in fact allows movement only along one direction at any instant in time, making it relatively easy to obtain a straight trajectory when acquiring 1-DoF targets.

Also results of amputee subjects show lower performance with the 3-DoFs control, and no significant difference between the two controllers in the main outcome measures. While for able-bodied subjects the R^2 values for empirical Fitts' law regression were around 0.9 in most cases (indicating that Fitts' law was appropriate), the R^2 values obtained by the amputee subjects during the PWR 3-DoFs control configuration trials were relatively low. This result could be due to the low number of amputee subjects, or could reflect lower control efficiency in the 3-DoFs control configuration as a consequence of the limb loss. However, the results of amputee subjects are significantly better with the 2-DoFs control configuration of PWR, improving completion rate, throughput and path efficiency compare to DC. It is worth to notice that the use of sEMG sensors could be a determinant factor. With respect to the results obtained with iEMG [23], amputee subjects performed much worse when using the 3-DoF control configuration with sEMG; for instance, completion times were more than double for all kinds of targets. This finding is hardly surprising, since intramuscular recordings can acquire signals from deep muscles and tend to be more reliable [41]. However, when amputee subjects used the 2-DoF control configurations in the virtual test, performance improved noticeably, with similar levels of path efficiency and simultaneous activation with respect to [23], for 1-DoF and 2-DoFs targets.

The results of the virtual test suggest to use only the 2-DoFs control configuration for the physical experimental evaluation. In the BBT, given the familiarity of the subjects with DC control and since we anticipated no need for switching DoF in this particular case, we expected DC to perform better than PWR. However, no significant difference was found between the two methods and the results obtained in the PWR trials were not dissimilar from the results obtained by state-of-art non-simultaneous algorithms for hand-wrist control in [42] and [43]. Moreover, when using PWR, subjects adjusted their wrist during the test to reach a more advantageous posture (the maximum wrist activation time was of 5.47 sec), while when using DC no adjustments were made (see Table VI), probably because adjusting the wrist would have entailed an unacceptable loss of time if compared to the foreseeable benefits. In the case of DC, the total absence of activation of wrist motion could be partially compensated by the hand compliance and adaptability, or by the introduction of compensatory movements, allowing to keep the performance satisfactory. Also in the results of the Cubbies Task, no significant difference emerged between the two controllers in terms of outcome measures. Similarly to BBT, subjects tended to use the wrist more when using PWR (see Table VI). The wrist activation reached the maximum time of 18.17 sec for the PWR, while 6.29 sec were registered for the DC. Despite the Cubbies Task had been specifically designed to provide an assessment of subjects' ability to control wrist flexion [40], some of the subjects were able to complete the task with minimal wrist adjustments or, in one case (TR4), no use of wrist flexion/extension at all. One reason could be that subjects preferred to exploit the grasp adaptability of the SHP instead of reaching the optimal angle between the hand and the blocks, but no qualitative evaluation of these aspects was conducted in this study. Finally, all of the subjects preferred PWR over DC, and during the subjective evaluation, they showed enthusiasm for the potential use of simultaneous control during daily life activities. One subject reported occasional unwanted co-activation of wrist and hand; however, as one subject (TR4) pointed out, simultaneous control of a prosthesis was new to them and probably with more practice they could have reached better mastery of the technique. Each experimental session lasted a maximum of four hours and future work should examine the learning of subjects over multiple sessions.

It is worth to notice that TMR surgery had probably an important role in the results of both experimental sessions. Subject TR4, the only participant who hadn't undergone TMR surgery, was the only subject not able to complete the virtual experiment in the 3-DoFs control configuration. The same user was the only participant able to perform better with DC in both assessment of the physical test. Moreover, TR4 made little or no adjustments of the wrist while using both controllers and had little hand-wrist simultaneous activation in the case of PWR. A possible explanation for this discrepancy of TR4 could be related to TMR surgery, but given the involvement of only one not-TMR subject in the study, it is not possible to generalize these findings.

In both experimental sessions, all subjects demonstrated the ability to use PWR to control simultaneously 2-DoFs, even after receiving little training and with results comparable to DC. As shown in Table IV, the average percentage of simultaneous activation for transradial amputees was higher compare to able-bodied subjects during the virtual test in the 2-DoFs configuration. Also during the physical test (see Table V) all subjects were exploring the simultaneous activation of hand-wrist and especially in the case of the Cubbies Task, specifically designed to promote a more active use of the wrist to avoid the introduction of considerable compensatory movements. The results of this preliminary investigation suggest that despite the performance of the two controllers are comparable, the PWR leads to a more active use of the wrist and consequently to a more natural grasp, while with DC the user tends to rely more on the hand itself and limits the use of the wrist only where strictly needed.

A limitation of this study is that the level of simultaneous control can be influenced by the choice of the prosthesis; future work will investigate the use of the PWR method on different combinations of DoFs and commercial hand prosthesis. In the authors' opinion, the grasp adaptability of the SHP could give the subjects great versatility during the tasks, and relax the constraints on the wrist configuration in some cases. Future studies will analyze how this affects the use of the wrist, along with improvement of algorithm robustness and a more extensive physical test, in order to realize the transition to a clinical solution.

V. Conclusion

This work explores the feasibility of using a PWR method with sEMG sensors. The PWR method, which had previously shown great performance in experiments with iEMG, was tested by eight able-bodied and four transradial amputee subjects in a virtual environment using sEMG, and performance compared with the one of a DC. Results show that, while using sEMG degraded performance for the 3-DoFs control, the algorithm demonstrated excellent performance in the 2-DoFs case. Then, the subjects with limb loss used PWR and DC to control a 2-DoFs hand-wrist prosthesis consist of a soft hand (the SoftHand Pro) and an active wrist (the RIC Wrist Flexor). The PWR method allowed the subjects to perform multi-DoF movements while maintaining the ability to isolate single DoFs for precise movements. Both subjective and objective measures indicate that PWR reached performance comparable to DC and encourage future investigations.

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