Online Classification of Transient EMG Patterns for the Control of the Wrist and Hand in a Transradial Prosthesis

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***Abstract*—Decoding human motor intentions by processing electrophysiological signals is a crucial, yet unsolved, challenge for the development of effective upper limb prostheses. Pattern recognition of continuous myoelectric (EMG) signals represents the state-of-art for multi-DoF prosthesis control. However, this approach relies on the unreliable assumption that repeatable muscular contractions produce repeatable patterns of steady-state EMGs. Here, we propose an approach for decoding wrist and hand movements by processing the signals associated with the onset of contraction (transient EMG). Specifically, we extend the concept of a transient EMG controller for the control of both wrist and hand, and tested it online. We assessed it with one transradial amputee and 15 non-amputees via the Target Achievement Control test. Non-amputees successfully completed 95% of the trials with a median completion time of 17 seconds, showing a significant learning trend ($p < 0.001$). The transradial amputee completed about the 80% of the trials with a median completion time of 26 seconds. Although the performance proved comparable with earlier studies, the long completion times suggest that the current controller is not yet clinically viable. However, taken collectively, our outcomes reinforce earlier hypothesis that the transient EMG could represent a viable alternative to steady-state pattern recognition approaches.**

***Index Terms*—Electromyography, human activity recognition, pattern recognition, prosthetic hand, virtual reality.**

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by Scuola Superiore Sant'Anna, Pisa, Italy Application No. 02/2017, and performed in line with the in accordance with the Declaration of Helsinki.

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I. Introduction

INTERPRETING the neurophysiological signals underlying voluntary motor control for driving limb prostheses represents a crucial, yet unsolved, challenge in applied neuroscience and rehabilitation engineering. Individuals with a below-elbow (transradial) amputation maintain part of the original musculature that served the digits and wrist. This allows for electromyography (EMG) recorded from extrinsic muscles in the forearm to be used as inputs to control a multi-degree of freedom (DoF) hand prosthesis, in a biomimetic manner [1]. While recent surgical techniques like Targeted Muscle Reinnervation (TMR) [2] and Regenerative Peripheral Nerve Interface (RPNI) [3] along with neuromusculoskeletal interfaces [4] or wireless Implantable MyoElectric Sensor (IMES) [5] implantation have shown the potential to restore accessibility to neural paths disrupted by the amputation, the use of EMG signals recorded from the skin surface remains today the most clinically viable approach for controlling transradial hand prostheses [6].

The most widespread controller available is substantially the two-state amplitude modulation EMG controller [7], in which a single pair of agonist/antagonist muscles directly controls the opening and closing of the hand (also termed *direct control*). This however cannot differentiate between different muscular patterns pertaining to different intended hand movements, and thus must be arranged in a sequential scheme, using special switching signals/inputs, to be used to control multiple grasps or DoFs of a dexterous prosthesis [8]. For example, following this approach to control a below-elbow prosthesis that includes a 1-DoF wrist and a 1-DoF hand, the user controls each DoF, one at a time, switching sequentially from one to the other.

EMG *pattern recognition* represents a viable alternative to direct control, as first proposed by Finley and Wirta in the late sixties [9]. It is based on the premise that amputees can voluntarily activate repeatable and distinct muscular contractions for each class of motion and the associated EMG patterns can be identified to send different commands to the prosthesis. Particularly relevant is the so called *continuous* classification pioneered by Englehart and colleagues [10]. In the latter, a set of statistical features emphasizing relevant structures in the EMG, during constant, somewhat steady-state contractions, is extracted from a continuous stream of signals using a sliding window, at a certain rate [11]. The features are then fed into a classification algorithm able to differentiate between patterns and produce a new decision (output of the classifier) at every time step, in a continuous fashion. Although such kind of classifier represents the state of the art [12], [13], its applicability in realistic settings, i.e., with different arm postures, grasps and force levels, remains to be solved [14], [15], [16].

Remarkably, the assumption that repeatable muscular contractions produce repeatable patterns of steady-state EMGs is unreliable and only statistically correct. The steady-state EMG has indeed a very little temporal structure (it approximates a random signal) due to the active modification of recruitment and of the firing patterns needed to sustain the contraction [17], [18]. On the contrary, the EMG associated with the onset of the myoelectric activity (i.e., the transient EMG) shows a more deterministic structure, likely due to the orderly recruitment of the Motor Units [19], [18]. In their study on prosthetic control, Hudgins and colleagues first observed that the transient EMG was shown to be descriptive of the intended movement [20].

Fascinated by these observations, and explicitly relying on the preplanned nature of grasping [21], in our recent study, we proposed an approach for decoding the intended grasp from the forearm EMG by processing the signals associated with the onset of muscular contraction [22]. We demonstrated that the muscle contraction associated with the initial enclosing phase of the grasp, contains indeed predictive information about the intended (and preplanned) grasp, which can be used in real-time to control a multi-grasp hand [23], [24]. In this work, we sought to further assess the potential of the transient approach by increasing the number of DoFs under control and porting the control strategy into an embedded controller. In particular, we implemented an online algorithm able to decode two DoFs in the wrist (flexion/extension, pronation/supination), and four grasp types in the hand (power, lateral, tri-digit, open), using only the portions of data associated to the onset of the muscular contraction. We claim that the inclusion of the wrist DoFs and the online assessment are two fundamental steps for assessing the viability of the proposed controller in a clinical implementation. Indeed, the inconsistency between offline and online performance [25], [26], [27], [28] and the relevance of the wrist district on prosthetic functionality [29] are well-known topics in the state-of-the-art.

We assessed this with 15 able-bodied participants and one transradial amputee while executing the TAC (Target Achievement Control) test to control a virtual hand on a computer screen, representative of an upper limb prosthesis which included a 2-DoF wrist and a multi-grasp hand [30], [31]. Non-amputee participants successfully completed almost all trials of the TAC test (completion rate $> 95\%$) with a median completion time of 17 s and with a significant learning trend ($p < 0.001$). The transradial amputee completed $\sim$80% of trials with a median completion time of 26 s. While these outcomes indicate that the proposed *transient controller* could potentially control a multi-DoF wrist-hand prosthesis, the long completion times in executing the TAC suggest that further assessments are necessary to fully evaluate its clinical viability. As an example, given that a learning effect was observed along with TAC test trials, the evaluation of participants performance within a multiday experimental protocol is desirable.

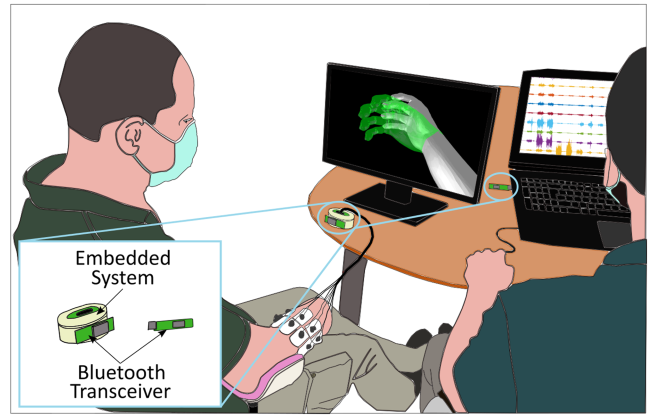

Fig. 1. Experimental setup. Eight pairs of surface electrodes were placed around the participants' forearms, while a custom embedded system acquired the signals and implemented the transient EMG controller. Raw signals as well as the outputs of the controller were sent wirelessly to a laptop via Bluetooth communication. The laptop ran the BioPatRec toolbox [31], used both for training the algorithm and running the virtual environment for the TAC test. The latter was displayed on a supplementary screen to the participant.

II. Materials and Methods

A. Participants and Experimental Protocol

One unilateral transradial amputee (male, age 56 years, 26 years after right arm amputation, 13 cm residual limb length) myoelectric hand user, and 15 non-amputees (aged 24–34, four females) with no known history of neuromuscular disorders, participated in the study. Informed consent in accordance with the Declaration of Helsinki was obtained before conducting the experiments from each participant. The study was approved by the local ethical committee of the Scuola Superiore Sant'Anna, Pisa, Italy (request no. 02/2017). The methods were carried out in accordance with the approved guidelines. The experimental setup consisted of a laptop computer running the TAC test [30], a custom embedded system [32] implementing the proposed transient EMG controller [22], eight surface differential electrodes, and a stand-alone monitor (Fig. 1). The surface electrodes were placed around the participants forearm in a cuff fashion, starting just distally to the elbow joint. The reference electrode was placed either on the olecranon or the elbow medial epicondyle, depending on the participant preference. EMG signals were acquired via the embedded system over Bluetooth wireless link with a 500 Hz sampling rate, and filtered via a 20 Hz second order Butterworth high-pass filter, a 250 Hz third order Butterworth low-pass filter, and a 50 Hz notch filter. Then, the embedded system extracted the mean absolute value (MAV) from windows of data of 100 ms with 50 ms overlap, and lastly executed the proposed classification scheme.

The participants were asked to perform the TAC test, i.e., to control the movements of a virtual hand shown on the PC screen to reach a target posture, by contracting their forearm muscles, while comfortably sitting (Fig. 1 and video clip in the supplementary materials) [30]. Building on our prior work where limb position was found not to significantly affect the performance of the transient EMG classifier [22], here we used only one limb position. This allowed to significantly reduce the number of trials and the overall test duration. More in detail, the test included 16 target postures involving combinations of four movements of the hand (power grasp, lateral grasp, tri-digit grasp, hand opening) and four movements of the wrist (flexion, extension, pronation, supination). Each target posture involved two movements of the wrist and one grasp (*e.g.*, wrist pronation, wrist flexion, and power grasp), and was presented three times. Thus, such TAC test assessed the capability of an 8-class classifier to achieve a combination of three random movements of hand and wrist for a total of 48 trials (4 hand movements × 4 wrist movements × 3 repetitions). The excursion of each movement was set to 40° in each target. The participants were given 45 s to reach the target posture (as in Simon et al. [30]); a trial was considered successful if the position of each of the controlled movements was at most ±5° away from the target, and maintained there for 2 s (dwell time, included in the 45 s). Vice-versa the trial was stopped and considered failed. The speed of the virtual hand was proportional to the EMG signals and ranged from 0 to 100 °/s (details below).

The proportional speed control of the virtual hand and wrist required some calibration. Before the TAC, for each movement under test, the maximum voluntary contraction (MVC) and a calibration/training dataset were collected. The latter included 20 repetitions for each of the eight movements. The averaged mean absolute value (aMAV) from all EMG channels was displayed as a biofeedback signal during the training. More in detail, the aMAV was displayed as a percentage of intensity between rest (0%) and the MVC (100%) of that specific movement. This aided the participants in producing similar (in amplitude) contractions among repetitions. The training procedure was managed using the BioPatRec toolbox for Matlab (R2017b, The Mathworks, Natick, MA, USA) [31].

During both the training and the test phases, performed during the same experimental session, participants were asked to sit on a chair with the elbow flexed at 90° on a soft cushion. Participants were instructed to contract their muscles at a moderate, non-fatiguing level (i.e., roughly around 40% of the MVC), and were allowed to rest when needed. Prior to testing, the participants familiarized with the TAC environment and controlled the virtual hand for at least 10 minutes. If the participant was not satisfied with his/her acquired control skills, the relative training signals were re-acquired.

B. Embedded Implementation of a Transient EMG Controller

In general, a transient EMG controller includes three main components: the *onset detection algorithm* (ODA), the classifier, and the proportional controller (Fig. 2). The ODA is responsible for detecting the onset of the muscle contractions, t_s, from rest. The classifier, fed with a window of signals starting from t_s and lasting $\mathrm{W_L}$ (i.e., 200 ms in the current study), is responsible for associating the EMG pattern to one of *N* possible movements. Finally, the proportional controller is responsible for modulating a certain parameter of the movement under control (*e.g.*, speed) based on the input signals. The following three paragraphs describe in detail how these components were implemented in the embedded system [32].

1) Onset Detection Algorithm: The ODA was based on a subject-specific threshold detector, calibrated offline using the derivative of the aMAV (daMAV). Specifically, the ODA relied on the daMAV to detect the beginning of an incipient muscular contraction. The calibration procedure started by defining 800 candidate-thresholds as equidistant values between a noise baseline (defined empirically as six times the standard deviation of

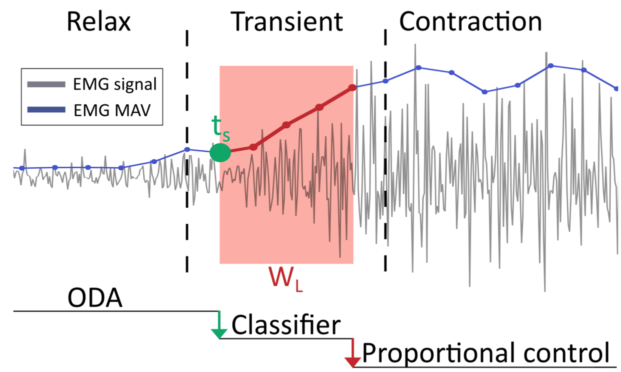

Fig. 2. Transient EMG controller components. The Mean Absolute Value (MAV) is extracted from the EMG signals and fed to the Onset Detection Algorithm (ODA). Once the ODA identifies an onset (at ts), the MAVs for a window (WL) are fed to a classifier; thereafter, the average of the (steady-state) MAV signals from eight electrodes is computed and used to proportionally modulate the output speed of the virtual hand/wrist movements.

the daMAV during rest) and the median of the peaks of all repetitions of a particular movement. Then, the movement-specific threshold was calculated as the mean of all candidate-thresholds that yielded the correct number of repetitions within the training set. Finally, the minimum value across movement-specific thresholds was used as the actual ODA threshold.

In this architecture, the output of the ODA signaled to the classifier the beginning of an incipient muscle contraction.

2) Classifier: We implemented a state of the art Error-Correcting Output-Codes classifier [33] with a one-versus-all coding matrix [34], comprising eight binary support vector machines (SVM) using a linear kernel. Unlike conventional continuous classification schemes, our classifier was fed with time series of EMG windows starting at $\mathrm{t_S}$ and lasting for 200 ms (i.e., $\mathrm{W_L}$) (Fig. 2), building on our previous study [22]. The classifier was fed with vectors that contained the temporal evolution of the signals, rather than only instantaneous patterns (i.e., composed of single values for each feature for each EMG window) as in conventional schemes [35]. In particular, it contained for each of the eight EMG channels, the MAV extracted from three consecutive windows (i.e., $\mathrm{MAV_{(t=50)}}$, $\mathrm{MAV_{(t=100)}}$, $\mathrm{MAV_{(t=150)}}$), for a total of 24 elements. In this way, the classifier provided an output (one out of eight classes) 200 ms after the identification of a muscle onset, whenever this was identified by the ODA. It should be noted, however, that the classification does not affect the MAV computation resolution (i.e., windows of 100 ms with 50 ms overlap), which affects the ODA and the proportional controller (described below). A finite state machine was implemented to maintain the output class as the active one (Fig. 3), and thus to control a specific movement (*e.g.*, wrist flexion or cylindrical grasp), as long as aMAV $> \mathrm{R_T}$ (rest threshold). Vice-versa, the finite state machine set the output class as a null class, not associated with any movement in the virtual prosthesis. $\mathrm{R_T}$ was identified akin to the selection of $\mathrm{t_s}$ for the ODA using the training dataset. The output of the classifier fed the proportional controller, responsible for modulating the speed of the movement in the virtual prosthesis, associated with the active class.

3) Proportional Controller: The proportional controller is responsible for modulating a certain parameter of the movement under control (*e.g.*, speed) based on the input signals. In this work, it linearly modulated the speed of the virtual hand/wrist

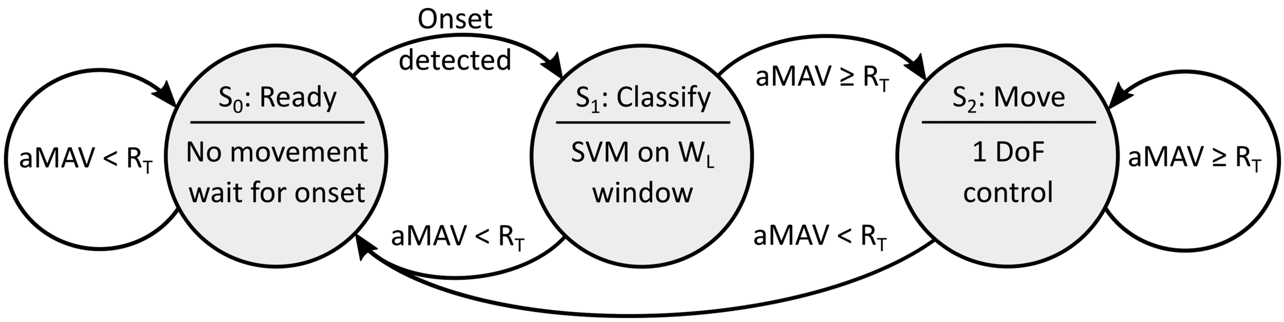

Fig. 3. Finite state machine regulating the transient EMG controller. Every 50 ms, the state of the system (circles) is updated based on the average of the MAVs (aMAV) or on the output of the Onset Detector.

movements depending on the contraction level of the participant, between zero and 100 °/s, as follows:

$$Prop_{out}(k) = \frac{1}{\#Ch}\sum_{i}^{\#Ch}\frac{MAV(i) - R_T}{MAV(i,k) - R_T} * 100 \qquad (1)$$

where k indicates the kth movement and the *MAV(i)* the MAV of the ith channel. The output was normalized between *MVC (i,k)* (i.e., the MVC of the ith channel of the kth movement), corresponding to 100% contraction (or speed), and $\mathrm{R_T}$, corresponding to 0% contraction (or speed).

C. Performance Metrics

From each trial of the TAC, we conducted a two-fold analysis by extracting both the accuracy of the online classification, as well as task-related metrics more closely describing the overall usability of the system. The definition of the accuracy of the classification was borrowed from the literature and adapted to the case of transient classification: it was computed as the ratio between the number of correct output movements over the total number of predicted movements [36]. More in detail, we considered as correct output any movement that reduced the distance between the target zone and the virtual hand driven by participants.

As for the task-related metrics we assessed those proposed by Simon et al. [30]: completion time (CT), completion rate (CR) and path efficiency (PE). The CT was the time from start to successful completion of a trial (including the dwell time); the CR was the percentage of successfully completed trials; the PE was the ratio between the shortest path for reaching the target divided by the total distance travelled by the virtual hand [30]. The shortest path was computed considering only sequential movements (i.e., single DoF activations). Moreover, as the shortest path was identified considering the nominal length of 40°, without the ±5° tolerance, it turned possible to achieve PE values greater than 100 %. In addition, in order to evaluate the control responsiveness, we assessed the time to the first correct class (TC) required to reach the first correct classification. Similarly, we also calculated the number of initial misclassification (IM) before the first correct classification. Similarly, we also calculated the number of misclassifications before (MB) the first correct one.

To verify if CT or PE showed a monotonic learning trend across trials data were analyzed by Spearman's rank correlation. A p-value lower than 0.5 was considered statistically significant. In the latter analysis, a CT of 45 seconds and a PE of 0% were assigned to failed trials.

III. Results

The overall test lasted between one and two hours, for each participant, mainly based on how many movements were required for retraining during the familiarization phase and on the performance during the TAC (in fact poor performance implied longer durations of each trial). Regarding non-amputee participants, no difference was observed between males and females.

Participants exhibited different behaviors in modulating the movements of the virtual hand. Although some of them preferred using a constant speed (the maximum allowed), eventually correcting overshoots, others modulated the velocity while reaching the target. Anecdotally, participants tended to reach the target posture by firstly operating the DoFs they felt easier to control, leaving the more difficult ones at the end.

Overall, the non-amputee participants achieved a remarkable online accuracy [82.1% median (7.2% IQR)] (Fig. 4(b)) and successfully completed almost all trials [CR: 95.8% (14.1%)] (Fig. 5) in a relatively short time [CT: 17.0 s (6.0 s)], and with a PE of 60% (17.7%). The amputee participant also demonstrated good classification accuracy [65.9% (18.0%)] (Fig. 4(b)) and controllability [CR: 81.2%, CT: 24.3 s (15.6 s), PE: 35.6% (16.8)]. While non-amputee participants successfully completed ∼60% of the trials within 20 s, the amputee participant did the same within 30 s (Fig. 5). The non-amputee participants selected the desired class almost at the first attempt [IM: 0 (0)] and with good responsiveness [TC: 0.9 s (0.75 s)]. Similarly, the amputee participant reported an IM of 0 (1) and a TC of 0.9 s (1.4 s).

Misclassifications proved equally distributed along the trial time for all participants (Fig. 4(a)). The Spearman's rank correlation coefficient revealed a learning trend with significative monotonic relation between the trial number and the median CT of non-amputee participants ($\rho^2 = 0.35, p < 0.001$) (Fig. 4(c)). Although weaker, the learning relation was significant between the trial number and the median PE as well ($\rho^2 = 0.19, p < 0.01$) (Fig. 4(c)). No significant trends were observed in the amputee participant, in neither the CT nor the PE across trials.

IV. Discussion

We implemented a transient EMG controller on a custom hardware embedded system and assessed its viability in controlling wrist and hand movements via the TAC test. In line with our previous work [22], we decided to use the SVM classifier to guarantee real-time implementation on a low-power portable platform, thus allowing future testing in unsupervised environments (i.e., at amputees' home). Indeed, while we know

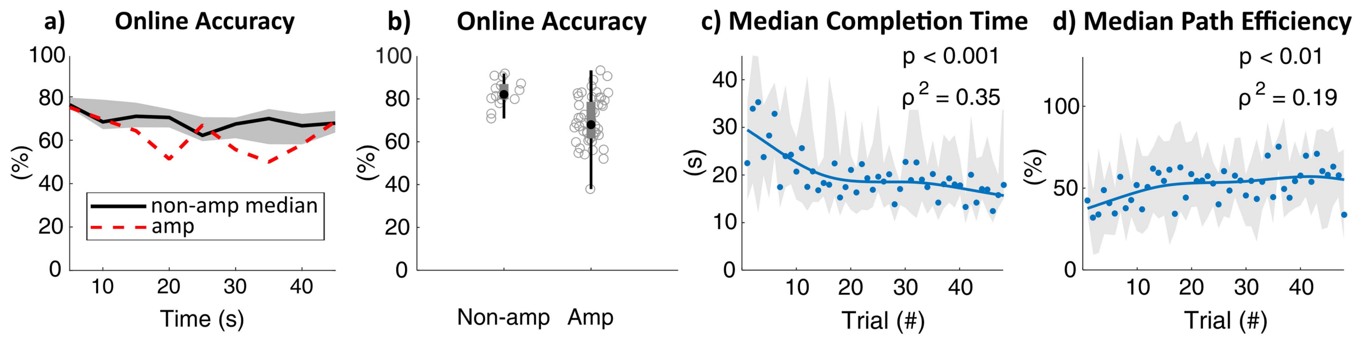

Fig. 4. Aggregated results. (a) Online accuracy as a function of time during the trial. (b) Box plot of the online accuracy for non-amputee participants (median from each participant – grey circles) and the amputee (all trials – grey circles). (c) Median completion time (blue dots) of non-amputee participants as a function of trial number. The median completion time significantly decreased with the trial number (Spearman's rank correlation). The grey area represents the interquartile range of each trial. The blue curve is a cubic spline interpolation of the median completion time. (d) Median path efficiency (blue dots) of non-amputee participants as a function of trial number. The grey area, the correlation test and the blue curve are defined analogously to the median completion time figure.

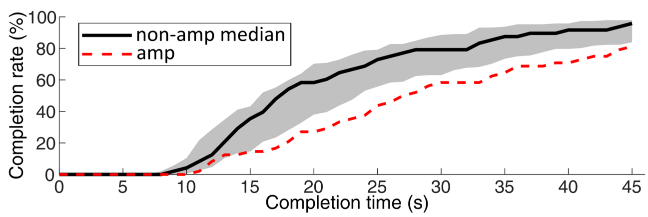

Fig. 5. Cumulative completion rate as a function of completion time. The curve indicates the percentage of trials completed in a certain amount of time. The black line and grey area represent the median performance and the interquartile range of the non-amputee group, respectively. The red dashed line represents the performance of the amputee.

that artificial neural networks could outperform the current implementation in terms of accuracy, they come at a higher computational cost in terms of both memory footprint and calculations. This implies the use of a more power demanding processor. Consequently, we opted for an SVM classifier to optimize the trade-off between the complexity and clinical relevance.

Concerning the control logic, although sequential movements, *prima facie*, could be considered as an unnatural control strategy, wrist and hand movements are in fact almost independent during normal reach-to-grasp, *i.e.*, they occur sequentially [37]. More in detail, while humans are probably used to simultaneously open the hand and rotate the wrist in reaching an object, prosthetic users arguably start the reaching phase with a prosthesis adequately opened in order to simplify the grasp planning. Building on this evidence, and on the importance of the wrist in natural grasping [29], [38], we deemed interesting to extend the concept of a transient EMG controller for the control of both wrist and hand, and tested it online. These two new experimental conditions allowed us to extend the assessment of the proposed transient EMG controller to a more realistic and complex scenario (i.e., more similar to the home use of a prosthesis). Hence, ensuring sufficient accuracy during the online classification of eight classes of movement (rather than four in offline settings [22]) represented the scientific challenge of this work.

Regarding the training dataset collection, while we acknowledge that often movements performed at different force levels are acquired [39], [40], here we instructed the participant to use a "moderate, non-fatiguing" force supported by the real-time biofeedback. Arguably, following the idea that the transient could anticipate the EMG signal part used for the proportional stage (i.e., the steady-state), we considered as uselessly fatiguing the possibility to acquire different force levels. We based this consideration on the outcomes of our previous work [22], which showed how the proposed transient EMG controller anticipates the steady-state phase of the EMG signal. Although our study included more movements than important prior works (8 vs. 6) [30], [41], we achieved almost comparable results in terms of CT and CR, and also observed a learning effect in non-amputee participants in the CT and PE over time (Fig. 4(c), (b)). Specifically, while the non-amputee participants included in our study reached similar performance to those reported in the work from Lv and colleagues [CT: 17.0 s (6.0 s) vs 20.9 s $\pm$ 3.4 s; CR: 95.8% (14.1%) vs 82.1% $\pm$ 8.2%] [41], our amputee showed a comparable CT and a slightly lower CR compared to the group of five amputees from the work of Simon and colleagues [CT: 24.3 s vs 20.1 $\pm$ 4.0 s; CR: 81.2% vs 92.1% $\pm$ 7.6%] [30]. In addition, the low values of IM and TC (that also included the participant reaction time) showed promising usability of the control system for both non-amputees [IM: 0 (0), TC: 0.9 s (0.75 s)] and the amputee [IM: 0 (1), TC: 0.9 s (1.4 s)] participants. Consequently, taken collectively, our outcomes reinforce earlier findings suggesting that the transient EMG controller could represent a viable alternative to more conventional pattern recognition approaches.

Yet, we argue that the achieved CT, as well as in the previous studies, proved far too long for considering the present setup, at least including eight hand and wrist movements, a clinically viable one. Nonetheless, the observed learning effect in non-amputee participants suggests that a multiday protocol could show more clinically viable performance.

The transient EMG controller exhibited a lower online accuracy compared to earlier studies in which the performance was assessed offline [82.1% (7.2%) vs 94.4% $\pm$ 2.8% [27] vs 96% $\pm$ 4% [41] vs 97.5% (2.6%) [42]]. Even in the case of the amputee, the online accuracy proved lower when compared to the offline performance reported by Simon and colleagues (65.9% vs 94.1% $\pm$ 3.1%), which performed the TAC test using basically the same online protocol [30]. Nonetheless, as mentioned above, although the complexity of our classification problem was greater than in Simon's study (8 classes vs. 6), we achieved comparable performance in terms of CT and CR. This apparent incongruency (*i.e.*, worse accuracy but similar online metrics) may be explained in two ways. First, although we borrowed the definition of *accuracy* from the literature, we had to adapt it for our transient classifier scheme, which unlike continuous classifiers provides an output only at the beginning of a contraction (and not at each window). Hence, in our definition the numerator and denominator are much lower figures than in a conventional continuous classifier, causing a lower statistical significance of the actual result when compared to the latter. In simple words, the comparison between accuracies should be carefully interpreted. Second, and not less importantly, our results corroborate the hypothesis that classification accuracy does not necessarily correlate with functional performance [25], [26], [27], [28], and invite studies in this area to always verify the online performance with the human in-the-loop. While we know that other works used TAC test for assessing the performance of continuous control strategies [12], [25], we mostly focused on Simon and colleagues work [30] because it was, at the moment of writing, the most comparable study with respect to the online performance of our amputee participant. For example, similarly to us, Catalan and colleagues assessed a sequential (and simultaneous) control strategy using a 3-DoFs TAC test obtaining better functional outcomes [30 s of timeout, considering the sequential controller – CR: 79.1 % (25.5 %) *vs* 92.0 s (16.0 s)]. However, they administered simpler tasks assessing a 6-class problem and used a considerably lower virtual hand maximum speed (i.e., 40 °/s vs the 100 °/s used here) [27].

In Simon and colleagues' work [30], the starting posture of the hand differed in every trial while the target posture was always the rest condition; here, as in Ortiz-Catalan and colleagues' study [27], we did the opposite. We argue that starting from a rest posture and reaching different target postures better mimics the use of an actual prosthesis. However, this may have decreased the interpretability of the virtual environment as it displayed a different target at each trial. Notably, a few participants actually claimed that when the controlled hand was close to the target it was difficult to understand which DoFs were or were not within the target zone, perhaps graphical updates in the TAC test interface can be beneficial. This last observation, as already claimed by Wurth and colleagues [43], makes the TAC test more difficult than other commonly used Fitt's law style assessment procedures (based on visual cues simpler than a virtual hand). Consequently, comparing functional outcomes across assessment methodologies is inappropriate.

For the group of non-amputees, while the majority of the trials (60%) were completed within 20 s, an additional 25 s proved necessary to reach a 95% CR (Fig. 5). This trend probably infers that each participant experienced greater difficulty in controlling specific movements, leading so to a prolonged trial when such movements were included in the target postures. A deeper analysis of this aspect did not retrieve generalizable difficult movements thus suggesting that they were participant-specific.

Some non-amputee participants and particularly the amputee controlled the speed of the virtual hand in an on/off fashion, sometimes producing a bouncing trajectory around the target posture, and as such a lower path efficiency (Fig. 4). This behavior could be due to three different factors. First, the modulation of the virtual hand speed was a more difficult task, as compared to operating it at full speed, and the TAC test did not provide a direct endorsement for it. Hence, some of the participants simply adopted the simpler strategy of correcting eventual overshoot errors rather than finely modulating the speed. This could likely be caused by the choice of the maximum speed, chosen to match with Simon et al.'s study for a direct and fair comparison, which perhaps proved excessive. Retrospectively, it is not surprising that other investigators actually chose a lower maximum speed to execute similar tests (i.e., 40 °/s) [27], [44]. Second, the output of the proportional control was computed giving equal weight to each of the eight EMG channels (1). In turn, if one channel had very low dynamics, and this was likely the case for the amputee, it could easily provide a very high contribution to the output, hence resulting in limited controllability. A potential solution could be to exclude the channels with low/lower EMG activity from the computation of the proportional output, yet keeping them for the classification. Third, the EMG envelope often showed an overshoot at the end of the transient phase, likely due to muscular recruitment mechanisms [45], [46], [47]. Such overshoot, mostly filtered out by a post-processing algorithm in continuous pattern recognition controllers [48], was the first input to the proportional controller and made it difficult to produce slow movements immediately after the muscular onset.

Although it allowed to uncover some practical aspects of the transient EMG controller/classifier, this study exhibited a few limitations that are worth discussing. First, it is known that multiple time-domain features improve the accuracy of the classification and that optimal feature sets do exist for continuous classifiers [35]. Nevertheless, building on our previous study [22], we used only the MAV, considering that the MAV of the raw EMG is known to be comparable to the output of commercial dry surface EMG electrodes (that are used in actual prostheses). This allowed us to assess the transient EMG controller with more realistic data. Second, our system/protocol allowed any movement (related either to the hand or the wrist district) to be executed at any time, with no pre-defined order. While this per se represented an asset, as it more closely resembled natural conditions, it also allowed the participants to execute the movements opportunistically, *i.e.*, controlling the closing of the hand before properly orientating the wrist. This, however, is not physiologic as in natural reach-to-grasp movements the orientation of the wrist typically anticipates the closure of the digits; hence the results present this bias. Third, the presence of a single amputee impeded us to draw any conclusion about an amputee population. Ultimately, the training session proved quite long and sometimes tedious for the participants. As a consequence of this, and of the poor results achieved with the group of non-amputees (in terms of CT), we decided to enroll a single participant with amputation. Since we did not anticipate significant experimental differences, we avoided recruiting and exposing multiple amputees to a potentially tedious/lengthy test. As suggested by Bunderson and Kuiken [49], a better experience/engagement could have been attained by providing the participants with a more accurate representation of the features space, such as the real-time bio-feedback.

Wrapping up, although the online performance proved comparable with other similar sequential controllers [27], [30], the completion times achieved with the current experimental protocol cannot be acceptable for a clinically viable system yet. We argue that any upper limb amputee, especially if unilateral, would not accept to take tens of seconds to properly orientate his/her prosthesis to grasp an object. Until the technology would not prove performance comparable to the sound limb, or at least restore lost functions which are not possible in other ways, such technology would likely be dropped [50]. In this case, compensatory movements with the more proximal segments would allow the person to achieve the same goal, not having to wear a slow (and perhaps expensive and heavy) prosthesis at all. However, while current single session outcomes suggest that an 8-classes sequential control over three movements of the wrist and the hand (wrist flexion/extension, pronation/supination, hand grasps) is not yet a viable option (3 DoFs tasks are completely mostly in 20 seconds), the observed learning trend suggested that the online performance could probably improve by letting the participants training across multiple sessions, eventually across days [51], [52]. Moreover, arguably, having simultaneous control of the two DoFs of the wrist in sequence with (followed by) the control of the grasp (as assessed by Amsuess and colleagues [53]), could reduce the completion times and represents a good trade-off between classifier complexity and control dexterity. This is in agreement with Smith and colleagues' basic study on simultaneous EMG control [54]. They argued that in a 2 DoF reaching task (*i.e.*, in a virtual Fitts' Law task) simultaneous control is typically used in the first phase for grossly reaching the target, whereas sequential control is preferred at later stages for precise, small adjustments [54]. In our controller, we did not consider simultaneous wrist movements as they would have implied a considerably longer training procedure to the participants (*i.e.*, 80 additional repetitions, for the training dataset) [12], [27], [43]. In fact, in the current methodology, the classification with the highest confidence level among the outputs of the eight binary one-versus-all SVM was selected as the intended movement. The selected scheme makes it impossible to perform simultaneous movements and imposes that any additional movement combination would require a dedicated set of repetitions to train the algorithm. However, although out of the scope of this study, the possibility to decode simultaneous wrist movements without increasing the dimension of the training set exists. For example, analogously to the work of Catalan and colleagues [27], the outputs of the single one-versus-all SVM could be combined into a simultaneous movement if the two DoFs of the wrist were both selected. Eventually, in order to ensure the reliability of the classification, an adequate confidence threshold should be set [55].

Taking these considerations collectively, desirable future investigations may comprise the design of an experimental protocol including testing on multiple days in order to assess the control stability longitudinally and fully evaluate the learning capability associated with the transient controller. Additionally, in order to include simultaneous movements but at the same time avoid the initial tedious/lengthy training session, a scheme with growing difficulty could be considered. More in detail, similarly to that proposed by Perry and colleagues [56], participants could start using a subset of movements (e.g., open/close and wrist pronation/supination) and add new ones gradually, in a multiday scenario, once that good controllability has been achieved.

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