Decoding of Multiple Wrist and Hand Movements Using a Transient EMG Classifier

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***Abstract*— The design of prosthetic controllers by means of neurophysiological signals still poses a crucial challenge to bioengineers. State of the art of electromyographic (EMG) continuous pattern recognition controllers rely on the questionable assumption that repeated muscular contractions produce repeatable patterns of steady-state EMG signals. Conversely, we propose an algorithm that decodes wrist and hand movements by processing the signals that immediately follow the onset of contraction (i.e., the *transient* EMG). We collected EMG data from the forearms of 14 non-amputee and 5 transradial amputee participants while they performed wrist flexion/extension, pronation/supination, and four hand grasps (power, lateral, bi-digital, open). We firstly identified the combination of wrist and hand movements that yielded the best control performance for the same participant (intra-subject classification). Then, we assessed the ability of our algorithm to classify participant data that were not included in the training set (cross-subject classification). Our controller achieved a median accuracy of ∼96% with non-amputees, while it achieved heterogeneous outcomes with amputees, with a median accuracy of ∼89%. Importantly, for each amputee, it produced at least one *acceptable* combination of wrist-hand movements (i.e., with accuracy > 85%). Regarding the cross-subject classifier, while our algorithm obtained promising results with non-amputees (accuracy up to ∼80%), they were not as good with amputees (accuracy up to ∼35%), possibly suggesting further assessments with domain-adaptation strategies. In general, our offline outcomes, together with a preliminary online assessment, support the hypothesis that the transient EMG decoding could represent a viable pattern recognition strategy, encouraging further online assessments.**

***Index Terms*— Myoelectric control, pattern recognition, transient EMG, hand wrist prosthetics, cross-subject classifier.**

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I. Introduction

DECODING neurophysiological signals produced by humans during voluntary motor tasks for controlling limb prostheses, in a seamless manner, is an essential yet unsolved challenge in applied neuroscience and rehabilitation engineering. People with a below-elbow (or transradial) amputation preserve in their residual limb the musculature originally serving the wrist and the hand. Hence, the interpreted electromyogram (EMG) acquired from such extrinsic muscles in the forearm, represents an ideal solution for controlling multi-degrees of freedom (DoF) hand prostheses, in a biomimetic manner [1], [2]. In the last two decades, the implementation of new surgical techniques allowing the implantation of myoelectric sensors or electrodes proved the possibility of restoring direct access to the neurophysiological paths disrupted by the amputation [1]. Nevertheless, the recording of surface EMG remains today the most widely spread, reliable, and clinically viable approach for controlling battery-operated transradial prostheses [3]. One of the most common approaches available today is substantially the two-state amplitude controller proposed by Bottomley in the 60's [4], in which the opening/closing of the motorized prosthetic hand (one DoF) is controlled using a pair of agonist/antagonist muscles (also termed *direct control*). Albeit relatively intuitive and simple to fit, its main limitation is that it can distinguish only between two opposite movement intentions (e.g. open and close), and therefore it fails to be intuitively extended to multi-DoF control in multiarticulated hand prostheses.

EMG *pattern recognition* represents a viable alternative to *direct control* and builds on the hypothesis that individuals with upper limb amputation can intentionally produce distinct and repeatable muscular contractions for different intended movements. In such application, a set of mathematical features is extracted from an array of EMG signals recorded during constant, somewhat steady-state contractions. These features are then fed into a classification algorithm previously trained to differentiate between patterns relative to different muscular contractions, thus producing a continuous stream of motor predictions meant to ultimately control the robotic hand [5].

A wealth of EMG pattern recognition systems has been proposed so far by the research community using several kinds of machine learning techniques [6]. Such systems are usually assessed in the vast majority via offline analysis [1], [6], and more rarely via online tests with both amputee and non-amputee participants [1]. Unfortunately, only a few reached a level of performance relevant for clinical translation [7], [8], and even less reached the commercialization stage [9], [10], [11]. Nonetheless, a few of the great promises of machine learning, namely, the possibility to: (i) learn how to deal with a range of different contractions, (ii) adapt to varying environmental conditions [12], [13], and (iii) generalize across different individuals, have been hindered by the stochastic nature of the picked up EMG signal. In fact, the assumption that repeated muscular contractions produce repeatable (mathematically describable) patterns of steady-state EMG is statistically weak, due to physiological reasons [14]. On the contrary, the EMG associated with the onset of the myoelectric activity (i.e., the *transient EMG*) shows a clearer temporal structure, likely due to the orderly recruitment of the motor units [14], [15]. Remarkably, in one of their studies on prosthetic control, Hudgins and colleagues first observed that the transient EMG was more descriptive of the intended movement than the steady-state EMG [16].

Inspired by Hudgins' original work, we recently proposed a computational framework for recognizing the grasp intention from the forearm EMGs associated with the onset of muscle contraction [17]. We found that the *transient EMG* phase can be indeed used for predicting/classifying the intended grasp type (power, lateral, bi-digital grasps, open movement) and for controlling multi-grasp prosthetic hands with remarkable real-time performance. In parallel, we also proved that the onset of contraction includes relevant information predictive of the pre-planned grip force [18] and can be extracted in real-time using a regression algorithm [19]. In this work, we sought to further investigate the potential and limitations associated with the transient EMG controller by assessing its classification ability on a more complex problem of eight classes, including both wrist (flexion, extension, pronation, supination) and hand movements (open hand and power, lateral and bi-digital grasps). To this aim, we collected EMG data from the forearms of 14 non-amputee and 5 transradial amputee participants while they performed the aforementioned eight movements. Through offline processing, we extracted the portions of data associated with the onset of the muscular contraction and processed these to identify the intended movements using a representative classifier (intra-subject analysis). In addition, one of the amputee participants preliminarily assessed the online performance of the proposed classifier by means of the target achievement control (TAC) test developed by Simon and colleagues [20].

Moreover, we assessed for the first time whether the informative content of the *transient EMG* could be used to train a cross-subject classifier, i.e., whether the data collected from multiple users could be used to train a classifier able to decode the movements of a new user (not present in the training set). The clinical appeal of this approach lies in the fact that, eliminating the need of collecting the new user data, would allow both to shorten the procedure for training the algorithm as well as to increase the control stability over multiple days [21], [22]. Cross-subject classification approaches were already investigated for conventional continuous classification schemes, i.e. using the steady-state phase of the EMG. These studies yielded to very different outcomes with accuracies ranging between 10% and 80% [21], [22], [23], [24], [25]. Such large variability seems to be due to the kind of movement under investigation: cross-classification proved acceptable for gross movements (like wrist movements or power grasps) [22], but rather modest for finer movements (e.g. precision grasp or individual digits movements) [21], [23]. Furthermore, suboptimal results have motivated the use of more complex mathematical approaches to pre-process the data in order to maximize the features space correlation across participants [22], [26], [27]. Those achieved by Sheng and colleagues, proved among the most promising outcomes, reaching an accuracy of $\sim$75% over seven classes (including wrist movements and the power grasp) and using data from six participants for training (LDA classifier) [22]. All in all, while machine learning proved capable to tackle the inter-subject variability as described by steady-state EMG patterns (at least for gross movements), it is still unknown whether the *transient EMG* could or not. Likely is unknown whether this may apply to the target population: to the best of our knowledge, cross-subject classification using signals collected from participants with amputations was never reported.

The intra-subject classification of the eight class problem exhibited a median classification accuracy of 96.2% (Inter Quartile Range (IQR) 5.6%) with non-amputee participants, and 89.2% (10.5%) with amputee participants. Moreover, at least one sub-combination of wrist and hand movements (from four to eight movements) with considerable accuracy ($>$85%) was found for each amputee participant [28]. In the preliminary online assessment, the amputee participant was able to successfully control the eight wrist and hand movements, completing 81.2% TAC test trials. Regarding the cross-subject classifier, the results for the eight class problem proved promising ($\sim$65% accuracy) for non-amputees, albeit rather poor for amputees ($\sim$30% accuracy), possibly due to the anatomical differences across amputations. However, we invite future studies in which implantable electrodes [29] and domain adaptation strategies [22], [26], [27] are used either to reduce or compensate for the inter-subject variability.

II. Materials and Methods

A. Participants and Experimental Protocol

Five unilateral amputees (three males) with a transradial short amputation (0% - 55% from the elbow [30]), myoelectric hand users (Table I), and 14 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

TABLE I
DEMOGRAPHIC DATA OF BELOW-ELBOW AMPUTEES

ID	Age	Years since Amputation	Cause	Side
A1	56	34	Traumatic	Right
A2	46	2	Traumatic	Left
A3	58	30	Traumatic	Right
A4	62	3	Ischemia	Right
A5	50	26	Traumatic	Right

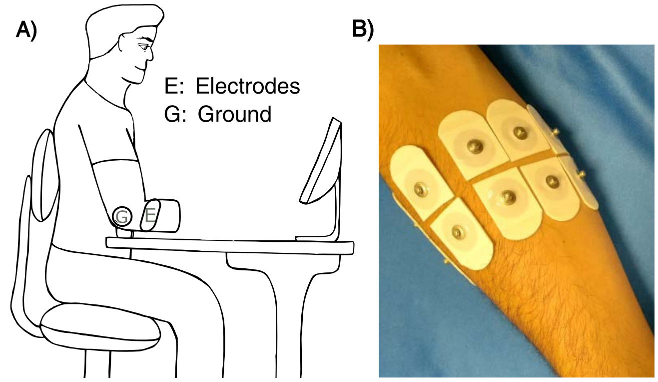

Fig. 1. Experimental setup. A) Participants sat on a chair with the elbow flexed at 90° on a cushion wearing a matrix of EMG electrodes and looking at a computer screen. The latter displayed in real time a biofeedback signal proportional to the average mean absolute value across the channels. B) Placement of the EMG electrodes around the forearm.

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.

Eight surface bipolar electrodes were placed around the participants' forearm in a cuff fashion, starting distally to the elbow joint with the ground electrode placed on the elbow (Fig. 1). The EMG signals were sampled by a custom acquisition device (500 Hz sampling rate, 20 Hz second order Butterworth high-pass filtered and 50 Hz notch filtered) [31] and sent to a laptop wirelessly (Bluetooth serial port). The participants sat on a chair in front of a computer screen with the elbows flexed at 90° on a soft cushion. As instructions were prompted on the screen, the participants were asked to contract muscles as to perform the eight different movements. Four were relative to the hand (power grasp, lateral grasp, bi-digital grasp, hand opening) and four to the wrist (flexion, extension, pronation, supination). Initially, participants were instructed to perform one repetition for each movement at the maximum voluntary contraction level (MVC). Then, they were asked to perform 20 repetitions of each movement, at a moderate, non-fatiguing force level (about 40% of the MVC), and were allowed to pause between each movement. Contemporarily, the average mean absolute value (aMAV) from all EMG channels was displayed in real time to the participant as a bar with variable length (0% representing rest, 100% representing MVC). This *biofeedback* signal helped the participants contracting their muscles in a repeatable fashion. Moreover, participants were asked to focus on intuitive and "natural" movements of the phantom limb (if any were perceived) while performing the muscular contractions. All instructions were provided verbally by the experimenter, then briefly verified with a few minutes training, and re-iterated if needed. The recorded EMG data was automatically labelled, stored, and analyzed offline.

Finally, a preliminary online assessment of the proposed controller was performed using the TAC test [20]. One of the amputee participants (i.e, A1) controlled the movement of a virtual hand shown on the PC screen (Fig. 1) to reach a target posture, by contracting his forearm muscles. The task included the execution of all movements included in the offline analysis.

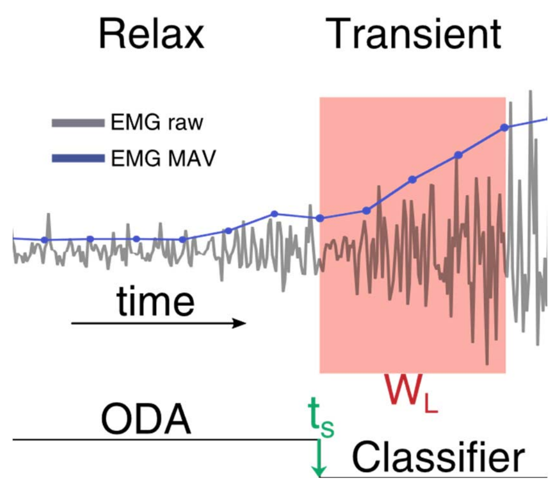

Fig. 2. Transient EMG classifier components. Once the Onset Detection Algorithm (ODA) identifies an onset (at t_S), the portion of EMG MAV (Mean Absolute Value) within the window W_L is extracted and fed to the classifier.

B. Transient EMG Classifier

A transient EMG controller was implemented in Matlab (R2017b, The Mathworks, Natick, MA, USA): albeit it is capable to operate online [17], it was used here for offline processing of the pre-recorded data. In the current implementation, the mean absolute value (MAV) was first computed from each EMG channel with a moving average filter (100 ms windows, 50 ms overlap). Then, an onset detection algorithm (ODA) was used to monitor the MAV time series in order to detect the onsets t_S of the muscular contraction and consequently trigger the classifier. Once an onset was found, the MAVs contained in a window starting at t_S and lasting for W_L (200 ms) were fed into a classifier (Fig. 2). The length of W_L was retrieved from our previous study [17].

Specifically, about the ODA, it was based on an individually calibrated threshold detector which relied on the derivative of the aMAV (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 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 to a number of rising crossings of daMAV equal to the number of repetitions within the training set. Finally, the minimum value across movement-specific thresholds was used as the actual ODA threshold.

The output of the ODA identified the beginning of the *transient EMG* phase and triggered the classifier. The latter was an Error-Correcting Output-Codes classifier with a one-versus-all coding matrix [32], comprising N binary support vector machines using a linear kernel, with N being the number of possible movements. The classifier was fed with time series of EMG windows starting at t_S and lasting for 200 ms, from which two different feature sets were extracted. The first (FS1) exploited widely used time domain features (i.e., MAV, zero crossing (ZC), waveform length (WL), slope sign changes (SSC) and root mean squared (RMS)) [16], the second (FS2) exploited the MAV extracted for three consecutive windows (i.e., $MAV_{(t=50)}$, $MAV_{(t=100)}$, $MAV_{(t=150)}$), building on our previous study [17]. FS1 was included to compare our method with the state-of-the-art steady-state EMG control techniques.

C. Offline Data Analysis

The data were processed offline using the BioPatRec toolbox for Matlab [33] and the classification accuracy was used as the performance metric. The definition of the accuracy was borrowed from the literature and adapted to the case of transient classification, by computing the ratio between the number of correctly predicted movements over the number of total predictions. Besides investigating the general performance of the transient EMG classifier, we sought to identify the best combinations of movements that could be decoded as well as the generalization capability, i.e., the ability to classify contractions by participants not included in the training set (cross-subject analysis).

A four-fold cross validation was used to assess the accuracy of the classifier. For each fold, the classifier was trained with 5, 10, or 15 repetitions per movement and tested using 5 repetitions. In all cases, the testing folds contained the same data. When 10 and 5 repetitions per movement were used for training, the training fold (which holds 15 repetitions per movement) was randomly down-sampled to the desired number of repetitions. While we analyzed the group performance for non-amputees and amputees using both FS1 and FS2, we performed the successive intra-subject analyses using FS2, in accordance with our previous study [17]. The number of training repetitions that yielded optimal global performance for FS2 was then used for assessing the performance achieved with different combinations of movements. Such combinations or subsets were inspired by those state of the art upper limb prostheses potentially capable of performing them [34]. Specifically, the following five combinations were evaluated: all movements (AM, 8 classes), hand grasps (HG, 4 classes), hand grasps plus wrist pronation/supination (HGPS, 6 classes), hand grasps plus wrist flexion/extension (HGFE, 6 classes), and hand open/close plus wrist movements (OCWR, 6 classes).

Finally, the ability of the transient EMG classifier to classify contractions by participants whose data were not included in the training set was investigated using a leave-one-subject-out cross validation. In particular, the relationship between accuracy and the number of participants included in the training set was assessed, in three cases: (i) training and testing on data from non-amputees (NA-NA), (ii) training and testing on data from amputees (A-A), and (iii) training on data from non-amputees and testing on data from amputees (NA-A). Also in this case, we analyzed the performance using both FS1 and FS2.

After evaluating the normality and homogeneity of the data, a one-way repeated measures ANOVA was used to determine statistical differences among the evaluated groups, with Bonferroni post-hoc correction. A p-value below 0.05 was chosen as the threshold for statistical significance.

D. Online Assessment

A1 executed the TAC test in a three-DoF task [20]. In this task, the 8-class (i.e., AM) classifier was trained with FS2 using the whole acquired dataset (i.e. 20 repetitions per movement). The wrist movements were combined with hand grasps for a total of 48 trials (4 grasps $\times$ 4 wrist movements $\times$ 3 repetitions). Analogously to the work of Simon and colleagues [20], the trial timeout, the dwell time, the maximum speed (proportional to the EMG signal amplitude), and the target width for matching the target were set to 45 s, 2 s, 100 °/s, and 5 °, respectively. To emulate as much as possible the usage of a real prosthesis we switched the target and the starting positions, initializing the trial from the neutral position instead of the position assumed after the execution of the three DoFs, differently from the work of Simon et al.

We assessed the functional metrics proposed by Simon et al. [20]: the completion time (CT), the completion rate (CR) and the path efficiency (PE). The PE was the ratio between the shortest path for reaching the target divided by the total distance traveled by the virtual hand [25].

III. Results

The performance of the classifier significantly increased with both the number of training samples and the number of features (i.e., FS1 vs FS2) (Fig. 3). In particular, for non-amputees, FS1 ranged from a median accuracy of 92.2% (8.7% IQR) with five repetitions, to a median of 96.2% (5.6%) with 15 repetitions, and FS2 ranged from a median accuracy of 85.9% (8.1% IQR) with five repetitions, to a median of 91.9% (3.7%) with 15 repetitions. Amputee participants performed worse, ranging from 80.5% (14.1%) to 89.2% (10.5%) for FS1 and from 75.6% (11.4%) to 81.6% (8.6%) for FS2. In non-amputees, the performance with 15 or 10 training repetitions proved statistically better than with five repetitions

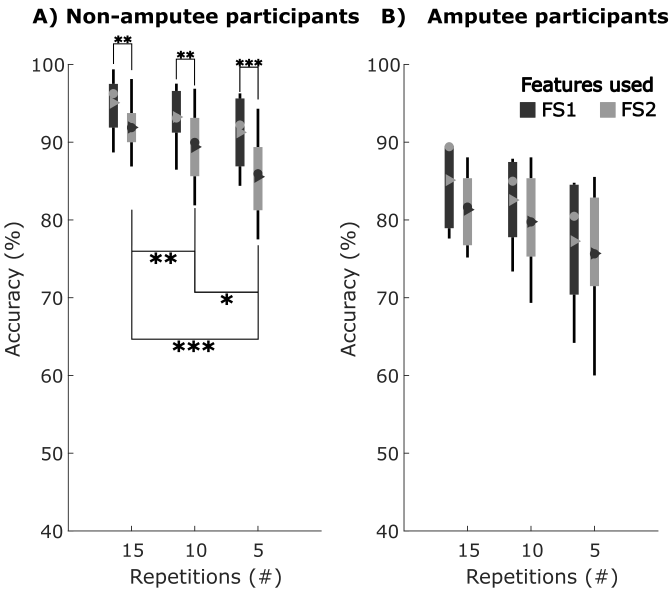

Fig. 3. Classification accuracy for different features and repetitions in the training set for non-amputee (A) and amputee participants (B). Features set 1 (FS1): mean absolute value (MAV), zero crossing, waveform length, slope sign changes and root mean squared). Features set 2 (FS2): MAV. Points and triangles represent median and mean values, respectively. Statistically significant differences, as determined by the Bonferroni post-hoc correction, are displayed (*: $0.05 \geq p > 0.01$; **: $0.01 \geq p > 0.001$; ***: $0.001 \geq p$).

($p<0.001$ and $p<0.05$, respectively); similarly, a statistical difference was found between 10 and 15 repetitions ($p<0.01$). Analogously, for both 5, 10 and 15 repetitions the performance proved significantly better using FS1 instead of FS2 ($p<0.01$). In amputee participants, both the training repetitions and the number of features did not yield to statistically different performances.

More in detail, in non-amputee participants, albeit all movements were seldom misclassified as the lateral and the bi-digital grasps, the overall performance proved rather consistent across classes and participants, exhibiting an accuracy of 91.9% for the 15 repetitions and FS2 (Fig. 4A). This was not the case in amputee participants, which demonstrated instead highly subjective results both in terms of overall and detailed (class-wise) classification (Fig. 4B-F). Nonetheless, some common behaviors emerged. For A3, A4 and A5, the open hand was rarely properly classified (31.6%, 36.8% and 47.2%, respectively) and frequently misclassified with the wrist extension movement. In addition, the bi-digital proved the most difficult to classify among the grasps, exhibiting an accuracy of 75.0%, 60.0%, 87.5%, 85.0%, and 70.0%, for A1, A2, A3, A4, and A5, respectively. Taken collectively the most misclassified movements concerned the wrist district, in particular flexion and extension. Interestingly, while for the amputees the supination was the most accurately classified movement (A1: 100%, A2: 100%, A3: 89.5%, A4: 95.0%, A5: 94.4%), it was actually the second worst (90.7%) for the non-amputee group (Fig. 4).

With respect to the combination of movements, in non-amputee participants, the median accuracy ranged from 91.9% (3.7%) for AM (all eight movements in the hand and wrist) to 96.7% (3.4%) for OCWR (hand open/close plus wrist movements) (Fig. 5A). The differences in performance proved to be statistically significant between OCWR and each of AM ($p < 0.001$), HGFE ($p < 0.01$), and HGPS ($p < 0.01$). Yet, the narrow IQR in each combination signified comparable behaviors (i.e., consistent outcomes) across participants.

In amputee participants, the accuracy spanned from 81.6% (8.6%) with AM to 91.2% (7.7%) with HG, albeit no statistical differences were found among the combinations, likely due to large variability in the data (Fig. 5A). More in detail, the individual performance of the amputee participants appeared highly subject-specific (Fig. 5B). As an example, HGFE yielded the best accuracy for A5 (85.3%) and A1 (86.7%) but the worst one for A3 (75.0%) (Fig. 5B). HGPS yielded exactly opposite outcomes, proving the worst configuration for A5 (82.6%) and the best for A3 (92.9%). Participant A1 proved the only one exhibiting a relatively high accuracy (>86.0%) for all tested combinations. All in all, at least one acceptable combination of wrist and hand movements (with accuracy >85.0%) proved possible for each amputee participant [28].

The cross-subject classification proved considerably worse than the intra-subject one (Fig. 4A vs. Fig. 6). However, the transient EMG classifier proved capable of recognizing muscle contractions of unseen non-amputee participants (NA-NA case) far beyond the random guess value (Fig. 6A). In other words, the system could be trained with EMG patterns from a number of non-amputees and fairly operate with a new non-amputee participant. For FS1 the accuracy increased with the number of (non-amputee) participants used in the training set, reaching a plateau of ~65% in the 8 class problem (AM in Fig. 6A), and a more promising ~80% in the 6 class problem (OCWR in Fig. 6A). The accuracy exhibited a high variability among participants as indicated by the IQR which ranged from 14.3% to 26.9% and from 11.3% to 27.6% for AM and OCWR, respectively.

The classifier barely succeeded in classifying EMG patterns from amputees when trained on non-amputees (NA-A) (Fig. 6B) and the same did when training on amputees and testing on unseen amputees (A-A) (not shown). Also in this case, for FS1, the data showed a large inter-subject variability with an IQR ranging from 5.6% to 17.4% and from 8.6% to 24.3% for AM and OCWR, respectively.

Regarding the preliminary online assessment, A1 promisingly completed the 81.2% of trials within 45 s (Fig. 7), with a median CT of 22.3 s (15.6 s). The PE of the completed trials was 35.6% (16.8%).

IV. Discussion

In this work, we further investigated the claim that the transient portion of forearm EMG signals, associated with the onset of a contraction, can predict the intended movements of upper limbs [17]. Specifically, we collected and classified data from 14 non-amputee and five transradial amputee participants while they performed eight movements relative to the hand and wrist districts. We assessed the ability of a support vector machine classifier in two scenarios: an intra-subject one, in which we identified the best combination of wrist

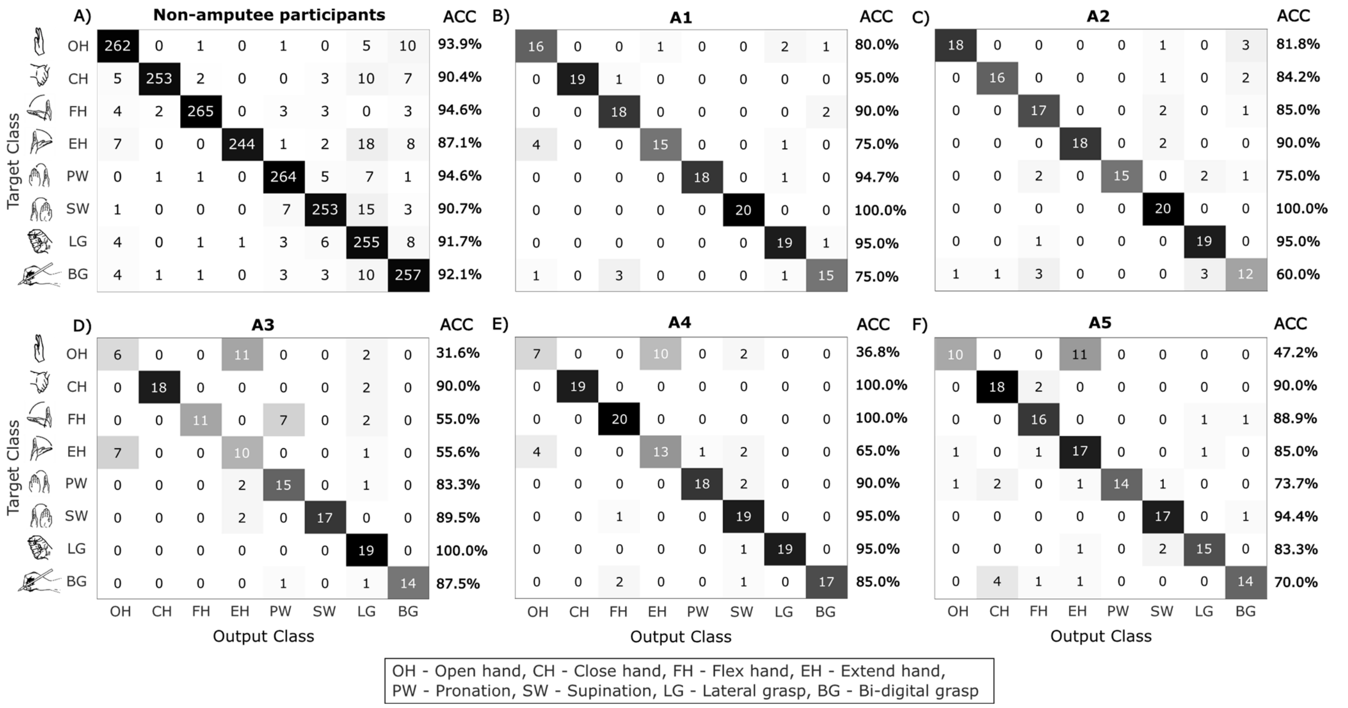

Fig. 4. Accuracy confusion matrices classifying EMG mean absolute values (i.e, FS2). A) Performance of non-amputee group. B-F) Individual performance of the amputee participants. The trials classified correctly are in the diagonal. The accuracy (ACC) of each class is indicated on the right of each matrix. The confusion matrices may be unbalanced either if the weaker contractions were included in the test set (the ODA cannot detect the onset) or if the participant did multiple contractions (the ODA detected more onset).

TABLE II
CLASSIFICATION ACCURACIES FOR STUDY BASED ON THE STEADY STATE OF EMG SIGNAL

Authors	Non amputees / amputees	Classes / EMG channels	Features	Classifier	Accuracy (non amputees / amputees) [Median (IQR) or Mean ± std]
This study All movements	14 / 5	8 / 8	MAV, ZC, WL, SSC, RMS	SVM	96.2% (5.6%) / 89.2% (10.5%)
Oskoei *et al.*, 2008 [37]	11 / 0	6 / 4	MAV, ZC, WL, SSC	SVM	96% ± 4%
Li *et al.*, 2010 [38]	0 / 5	11 / 12	MAV, ZC, WL, SSC	LDA	94% ± 3% (intact arm) / 74% ±11% (amputated arm)
Scheme *et al.*, 2011 [28]	10 / 5	11(non amputees), 5 (amputees) / 12	MAV, ZC, WL, SSC	LDA	96% ± 3% / 89% ± 3%
Catalan *et al.*, 2014 [36]	20 / 0	11 / 4	MAV, ZC, WL, SSC	LDA	95.7% (2.6%)
Adewuyi *et al.*, 2015 [35]	9 / 4 (partial hand amputees)	7 / 7	MAV, ZC, WL, SSC, 6^{th} AR	LDA	92% ± 2% / 83% ± 6%

IQR: Inter Quartile Range, std: standard deviation.
MAV: Mean Absolute Value, ZC: Zero Crossing, WL: Waveform Length, SSC: Slope Sign Change, RMS: Root Mean Squared, 6^{th} AR: six coefficients of a sixth order autoregressive model, SVM: Support Vector Machine, LDA: Linear Discriminant Analysis.

and hand movements, and a cross-subject one, where we assessed the ability to classify movements by participants not included in the training set. Furthermore, for both scenarios, we analyzed the change in performance by changing the dimension of the training set. Finally, one of the amputee participants preliminarily assessed the online performance of the proposed classifier in a virtual environment.

A. Intra-Subject Analysis

Our results proved performance comparable to studies based on the steady state of EMG signals that classify a similar set of movements using almost the same features (i.e, FS1) and with classifiers of comparable complexity (Table II) [28], [35], [36], [37], [38]. In addition, the performance of transient and steady state classifiers should be carefully compared: while in the former case the "rest" class is not considered in the overall accuracy, in the latter it often represents a bias (i.e., with considerably high accuracy).

In our previous work the transient EMG classifier was capable to classify four hand movements using the FS2 with an overall classification accuracy of ~95 % with non-amputees, and ~95% with two amputees [17]. Here, we have increased the complexity of the problem (eight classes vs. four) adding four wrist movements and achieved contradictory results: data from non-amputees reached similar classification accuracies

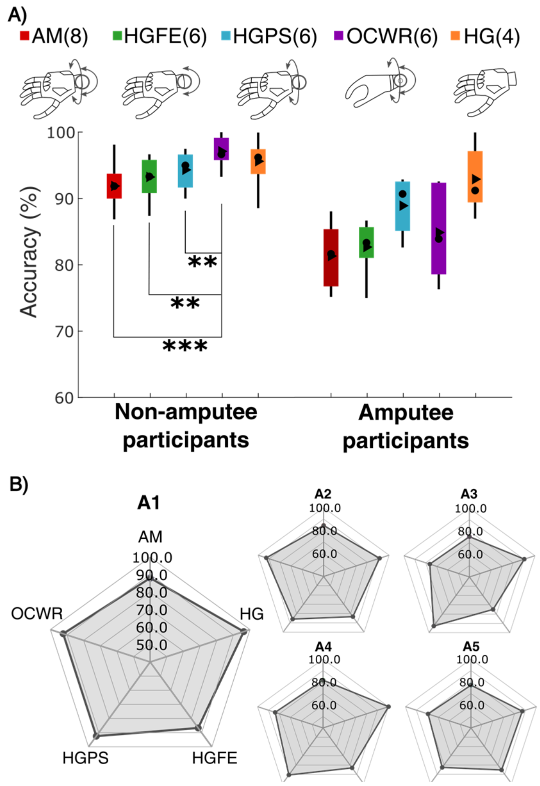

Fig. 5. Classifier accuracy for different combinations of movements classifying EMG mean absolute values (i.e, FS2). A) Performance for both non-amputee and amputee groups. Points and triangles represent median and mean values, respectively. Statistically significant differences, as determined by the Bonferroni post-hoc correction, are shown (*: $0.05 \geq p > 0.01$; **: $0.01 \geq p > 0.001$; ***: $0.001 \geq p$). B) Amputees' individual performance. Each vertex of the pentagon corresponds to a different combination of movements: AM (all eight movements in the hand and wrist; 8 classes), HGFE (hand grasps plus wrist flexion/extension; 6 classes), HGPS (hand grasps plus wrist pronation/supination; 6 classes), OCWR (hand open/close plus all wrist movements; 6 classes), HG (hand grasps; 4 classes).

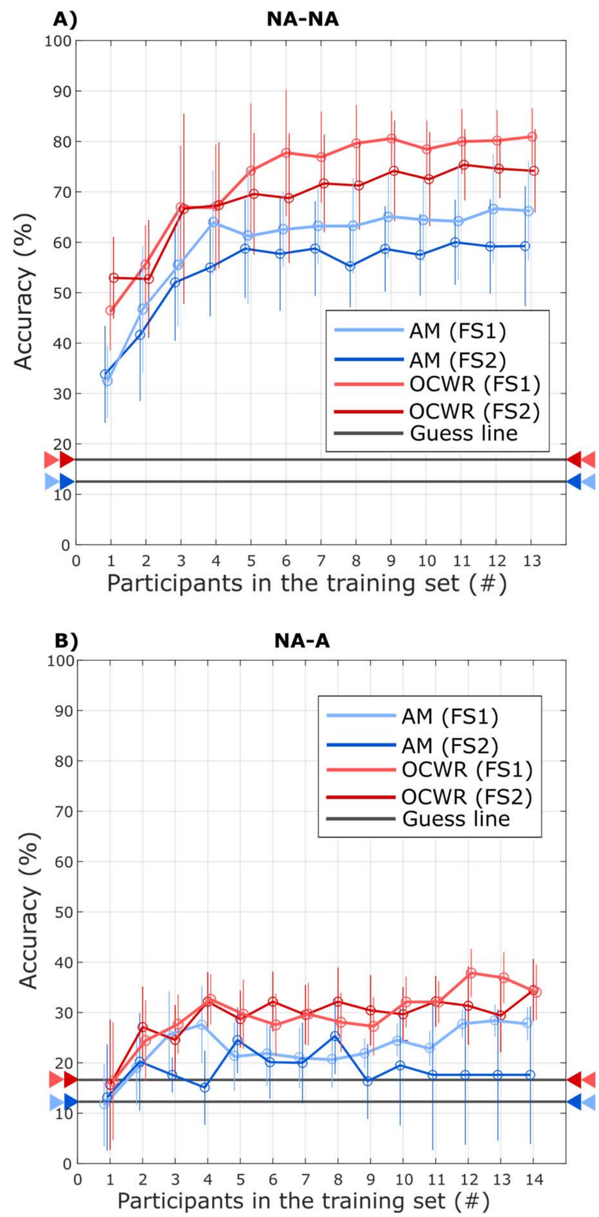

Fig. 6. Accuracy of the cross-subject classifier (AM and OCWR movement subsets) w.r.t. the number of participants' data included in the training set. Feature set 1 (FS1): mean absolute value (MAV), zero crossing, waveform length, slope sign changes and root mean squared). Feature set 2 (FS2): MAV. A) Accuracy of non-amputee participants using unseen data from non-amputees participants (NA-NA). B) Accuracy of amputee participants using unseen data from non-amputees participants (NA-A). The random guess values for AM and OCWR are also displayed (horizontal lines).

(∼92%) while data collected from amputees did not (∼82%). However, when considering the same set of four movements (here, so called HG) the performance of amputees proved comparable, suggesting a difference between the two groups.

As expected from the state of the art, FS1 outperformed FS2 [39] (Fig. 3). Nevertheless, building on our previous study [17], we evaluated a feature set that included only the MAV because it is known to be comparable to the output of commercial dry surface EMG electrodes (that are used in real prostheses). This allowed us to infer the applicability of our outcomes to a more applicative scenario.

Not surprisingly, the classification accuracy increased with the training repetitions (in a statistically significant manner for non-amputees) (Fig. 3) and the best median accuracies were achieved with 15 repetitions per movement. If compared with continuous classifiers, this represents a considerably higher number of training repetitions [36]. Of course, this is due to the inherent nature of a transient in an incipient muscular contraction (i.e., single onset/transient thus single sample) as opposed to continuous classifiers in which the steady-state phase is segmented in several windows, allowing to extract several training samples from just a few contractions (typically three or four). Hence, while 15 repetitions for training would surely represent a substantial effort for the individual, it must be also noted that the system proved fairly good even with five repetitions. We speculate that this extra burden during the training phase could be paid off during the online use of the system, given that the response time of a transient classifier is intrinsically shorter than continuous classifiers [17] and that the transient controller should arguably be more user

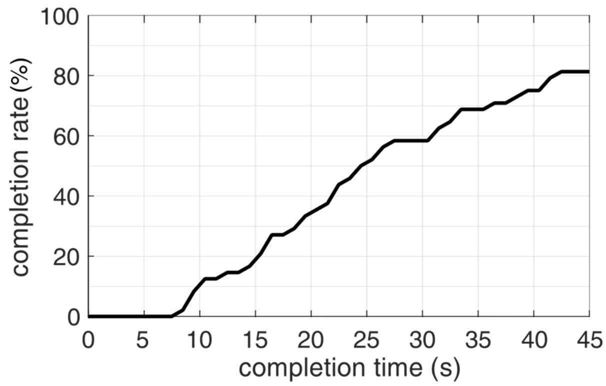

Fig. 7. TAC test performance of the amputee participant (i.e, A1). The curve indicates the percentage of trials completed in a certain amount of time.

friendly. Indeed, while steady state controllers continuously update the classification, hence requiring certain cognitive and muscular efforts from the user to maintain the myoelectric pattern, the transient controller keeps the class-output constant after the transient phase, thus allowing the user to focus only on the following proportional control phase (if any). Moreover, the transient controller inherently does not need post-classification algorithms (e.g., majority vote [40]), thus reducing its computational burden as well as its user-perceived response time. Finally, it is quite likely that a longer user training could even reduce the minimum number of repetitions yielding to acceptable accuracy [41].

The misclassification of wrist extension in open hand movements and vice-versa, common to the group of amputee participants (Fig. 4E-F), could be explained bearing in mind the control scheme of their personal myoelectric hand. As the contraction of wrist extensors is typically used for opening the prosthetic hand, it is plausible that they struggled in correctly differentiating between the two movements. In addition, we speculate that the extrinsic muscles that originally served the digits may have likely adhered to each other due to, e.g., atrophy or as a result of the amputation surgery, thus needing a longer training time to produce consistent differentiated contractions [42]. In light of this, a longitudinal evaluation of the control would be desirable.

Regardless of the group of participants, the assessment of the performance achieved with the different combinations of movements suggests that the number of classes did not affect the performance of the classifier as much as the choice of the movements (Fig. 5A). OCWR (hand open-close plus wrist movements, 6-classes) not only proved better than AM (all movements, 8-classes) but also than HGFE and HGPS (both with 6-classes) (Fig. 5A). The analysis underlined that the bi-digital and the lateral grasps were the most misleading movements for the classifier (Fig. 4A). Anecdotally, such misclassifications were uniformly distributed across participants and may be attributed to the anatomy of the proximal part of the forearm, i.e., where the electrodes were placed. For instance, the *flexor pollicis lungus* which is the main muscle involved in thumb flexion, thus in the lateral grasp, lies under the *extensor carpi radialis* which serves wrist extension [43], [44]. Hence, it is plausible that a wrist extension in a radial direction could generate EMGs misclassified with those of a lateral grasp. Same considerations may apply for the *flexor pollicis lungus* and the *supinator* to explain the misclassification of wrist supination with the lateral grasp. Although wrist extension and supination were often misclassified as the lateral grasp, the opposite did not occur. Perhaps, this may be explained by the fact that the lateral grasp was often performed in a mostly isometric condition (with the thumb in contact with the index before the beginning of a contraction actually detectable by the ODA) producing, hence, more repeatable patterns, whereas the wrist extension and supination were performed moving the upper limb (a dynamic contraction).

While the performance of A2, A3, A4 and A5 for different movement combinations (Fig. 5B) seemed to indicate a negative correlation with the time from the amputation, A1 proved the most performing participant although owning the oldest amputation. Hence, analogously to other studies [45], [46], the time factor alone could not explain lower performances.

B. Cross-Subject Analysis

Fascinated by the hypothesis that the deterministic structure exhibited by the transient EMG [15], [16] could present common features across individuals, we sought to assess the potential of a *transient* EMG cross-subject classifier. The results considering only non-amputee participants (NA-NA) showed promising results, in line with the 6 class problem studied by Sheng and colleagues (Fig. 6A, OCWR: ∼80% accuracy) [22], to our knowledge the only methodologically comparable study. Here, as the forearms of non-amputees did not significantly differ in size and the placement of the surface electrodes was standardized, the latter could roughly target the same muscles across the participants and thus pick up consistent signals. The large performance difference between AM and OCWR in decoding FS2 (even larger than in the intra-subject scenario), suggests that the bi-digital and the lateral grasps not only proved the most confounded ones within-subjects but also across-subjects. This aligns with earlier studies that used the steady state phase of the signal [21], [22], [23], [24], [25] and confirms –for the transient phase as well– that the contractions associated with digit movements across humans may be less similar to each other than the contractions produced during wrist movements.

The poor performance achieved when trying to classify amputee data (NA-A and A-A), roughly ∼30% for AM and ∼35% for OCWR (Fig. 6), suggests the approach cannot be applied straightforwardly with over-simplistic methods in the acquisition and processing of the data. The obvious anatomical differences that may exist between amputations (with a variable number, combination, and placement of the residual muscles), imply that properly operating a cross-subject classifier might require targeting specific muscles with the surface electrodes or, even better, use implanted electrodes [29]. This statement is supported by the outcomes achieved in the NA-NA case, where the anatomical differences were virtually cleared: in that case, indeed, the cross-classification accuracy proved significantly better. With respect to the processing of the data, domain adaptation techniques could be used to maximize the features space correlation across individuals and consequently reduce the number of training samples collected from a new user to train the classifier [22], [26], [27]. In this scenario, the domain of the general model (i.e., the general informative content) could be adapted to the new user by exploiting only a few contraction samples. Our intention here was to provide a reference baseline to researchers investigating domain adaptation strategies for cross-subjects generalization.

Luckily, implantable electrodes are becoming a reality [29], [47], whereas the networking, cloud computing, and data sharing infrastructures of the IoT are already important parts of our lives. Hence, it might be no longer impossible to envisage fleets of interconnected prostheses with learning and adaptive control systems.

C. Online Assessment

Although in our preliminary evaluation we included more movements (8 *vs* 6), A1 performed similarly to the five participants evaluated within Simon and colleagues' work [20] in term of CT [median 22.3 s *vs* 20.1s $\pm$ 4.0s] and CR (81.2% *vs* 92.1% $\pm$ 7.6%). Conversely, increasing the number of movements seemed to affect the PE, which worsened with respect to Simon's study [35.6% vs 54.7% $\pm$ 11.1%]. Hence, we could speculate that the increment of the available movements may have increased the total distance covered by the virtual hand controlled by the participant, while maintaining a comparable completion time. Arguably, the participant adopted an higher velocity with respect to the Simon's work. Anyway, while these preliminary results are somehow promising, we know that they cannot be considered as a validation of the proposed controller, which necessitates an assessment with a wider cohort of amputee participants with either a virtual device or, desirably, with a real one (i.e. a self-suspending prosthesis).

While it supported the transient EMG classifier as a viable alternative to continuous classification, this study exhibited a few limitations that are worth discussing. First, the current system implementation requires the participant to always return to the rest state before changing to the next desired output. While this limit could be overcome in future implementation (e.g. studying phase transitions between different movements), we speculate that it only partially affects the clinical application of the algorithm. Arguably, a "rest break between grasps" is already quite common in users of commercially available continuous pattern recognition systems, and this is particularly true in case of misclassifications (i.e. the prosthesis moving to an unwanted grasp). It is a simple measure, often recommended by occupational therapists during training, that can greatly improve the grasp selection accuracy. Moreover, we are aware that offline results provide limited insight about control usability and reliability. However, the aim of this work was to demonstrate the feasibility of the transient approach and, for the first time, offline performance comparable to state-of-the-art continuous pattern recognition controllers. Specifically, in the context of decoding wrist-hand movements in intra-subject and cross-subject problems. Our preliminary, but still promising, online results point to the mandatory successive step of online validation with a wider amputees population, with both virtual and real-world functional assessments. Additionally, it remains of interest to further explore and validate the cross-subject scenario for the non-amputee population, as this has the potential for human-machine interfaces for consumer and entertainment purposes [48].

V. Conclusion

In this work, we proposed a pattern recognition controller based on the transient portion of the EMG signal. With the proposed strategy that aimed at decoding several combinations of wrist and hand movements we obtained performances comparable to state-of-the-art steady-state EMG controllers. In addition, the accuracy of our algorithm was greater than 85% with at least one of the proposed movement combinations with amputee participants, despite the heterogeneous group performance (Fig. 5B). Last but not least, a preliminary online assessment into a virtual environment encouraged further evaluations with amputee participants.

This work opens doors for prosthetic control using the transient portion of the EMG, bringing the potential benefits of increased responsiveness and repeatability of the myoelectric prostheses, thus ultimately of improved quality of life for many amputees.

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References

[1] A. D. Roche, B. Lakey, I. Mendez, I. Vujaklija, D. Farina, and O. C. Aszmann, "Clinical perspectives in upper limb prostheses: An update," *Current Surg. Rep.*, vol. 7, no. 3, pp. 1–10, Mar. 2019.

[2] A. Furui et al., "A myoelectric prosthetic hand with muscle synergy–based motion determination and impedance model–based biomimetic control," *Sci. Robot.*, vol. 4, no. 31, Jun. 2019, Art. no. eaaw6339.

[3] N. Jiang, S. Dosen, and D. Farina, "Myoelectric control of artificial limbs—Is there a need to change focus? [In the spotlight]," *IEEE Signal Process. Mag.*, vol. 29, no. 5, pp. 152–150, Sep. 2012.

[4] A. H. Bottomley, "Myoelectric control of powered prostheses," *Bone Joint J.*, vol. 47, no. 3, pp. 411–415, 1965.

[5] M. Zecca, S. Micera, M. C. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Crit. Rev. Biomed. Eng.*, vol. 30, nos. 4–6, pp. 459–485, Jan. 2002.

[6] M. Ison and P. Artemiadis, "The role of muscle synergies in myoelectric control: Trends and challenges for simultaneous multifunction control," *J. Neural Eng.*, vol. 11, no. 5, Oct. 2014, Art. no. 051001.

[7] L. J. Hargrove, L. A. Miller, K. Turner, and T. A. Kuiken, "Myoelectric pattern recognition outperforms direct control for transhumeral amputees with targeted muscle reinnervation: A randomized clinical trial," *Sci. Rep.*, vol. 7, no. 1, pp. 1–9, Dec. 2017.

[8] E. Mastinu, J. Ahlberg, E. Lendaro, L. Hermansson, B. Hakansson, and M. Ortiz-Catalan, "An alternative myoelectric pattern recognition approach for the control of hand prostheses: A case study of use in daily life by a dysmelia subject," *IEEE J. Translational Eng. Health Med.*, vol. 6, pp. 1–12, 2018.

[9] Ottobock U.S. *Myo Plus | Ottobock U.S.* Accessed: Mar. 20, 2022. [Online]. Available: https://www.ottobockus.com/prosthetics/upper-limb-prosthetics/solution-overview/myo-plus/myo-plus.html

[10] L. Coapt. *Pattern Recognition—Coapt, LLC*. Accessed: Mar. 20, 2022. [Online]. Available: https://coaptengineering.com/pattern-recognition

[11] L. Infinite Biomedical Technologies. *Sense—Infinite Biomedical Technologies*. Accessed: Mar. 20, 2022. [Online]. Available: https://www.i-biomed.com/sense.html

[12] J. L. Betthauser et al., "Limb position tolerant pattern recognition for myoelectric prosthesis control with adaptive sparse representations from extreme learning," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 4, pp. 770–778, Apr. 2018.

[13] M. Vidovic, H.-J. Hwang, S. Amsuss, J. Hahne, D. Farina, and K.-R. Müller, "Improving the robustness of myoelectric pattern recognition for upper limb prostheses by covariate shift adaptation," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 9, pp. 961–970, Sep. 2015.

[14] R. Merletti and P. A. Parker, *Electromyography: Physiology, Engineering, and Noninvasive Applications*, vol. 11. Hoboken, NJ, USA: Wiley, 2004.

[15] Y. Yamazaki, M. Suzuki, and T. Mano, "An electromyographic volley at initiation of rapid isometric contractions of the elbow," *Brain Res. Bull.*, vol. 30, nos. 1–2, pp. 181–187, 1993.

[16] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 1, pp. 82–94, Jan. 1993.

[17] G. Kanitz, C. Cipriani, and B. B. Edin, "Classification of transient myoelectric signals for the control of multi-grasp hand prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 9, pp. 1756–1764, Sep. 2018.

[18] I. J. R. Martinez, A. Mannini, F. Clemente, A. M. Sabatini, and C. Cipriani, "Grasp force estimation from the transient EMG using high-density surface recordings," *J. Neural Eng.*, vol. 17, no. 1, Feb. 2020, Art. no. 016052.

[19] I. J. R. Martinez, A. Mannini, F. Clemente, and C. Cipriani, "Online grasp force estimation from the transient EMG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 10, pp. 2333–2341, Oct. 2020.

[20] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "Target achievement control test: Evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses," *J. Rehabil. Res. Dev.*, vol. 48, no. 6, pp. 619–628, 2011.

[21] T. Tommasi, F. Orabona, C. Castellini, and B. Caputo, "Improving control of dexterous hand prostheses using adaptive learning," *IEEE Trans. Robot.*, vol. 29, no. 1, pp. 207–219, Feb. 2012.

[22] X. Sheng, B. Lv, W. Guo, and X. Zhu, "Common spatial–spectral analysis of EMG signals for multiday and multiuser myoelectric interface," *Biomed. Signal Process. Control*, vol. 53, Aug. 2019, Art. no. 101572.

[23] M. Stachaczyk, S. F. Atashzar, S. Dupan, I. Vujaklija, and D. Farina, "Toward universal neural interfaces for daily use: Decoding the neural drive to muscles generalises highly accurate finger task identification across humans," *IEEE Access*, vol. 8, pp. 149025–149035, 2020.

[24] M. Georgi, C. Amma, and T. Schultz, "Recognizing hand and finger gestures with IMU based motion and EMG based muscle activity sensing," in *Proc. BIOSIGNALS 8th Int. Conf. Bio-Inspired Syst. Signal Process., 8th Int. Joint Conf. Biomed. Eng. Syst. Technol. (BIOSTEC)*, 2015, pp. 99–108.

[25] C. Castellini, A. E. Fiorilla, and G. Sandini, "Multi-subject/daily-life activity EMG-based control of mechanical hands," *J. Neuroeng. Rehabil.*, vol. 6, no. 1, pp. 1–11, Dec. 2009.

[26] U. Côté-Allard et al., "Deep learning for electromyographic hand gesture signal classification using transfer learning," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 4, pp. 760–771, Apr. 2019.

[27] R. N. Khushaba, M. Takruri, J. V. Miro, and S. Kodagoda, "Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features," *Neural Netw.*, vol. 55, pp. 42–58, Jul. 2014.

[28] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *J. Rehabil. Res. Develop.*, vol. 48, no. 6, pp. 643–660, 2011.

[29] S. Salminger et al., "Long-term implant of intramuscular sensors and nerve transfers for wireless control of robotic arms in above-elbow amputees," *Sci. Robot.*, vol. 4, no. 32, 2019, Art. no. eaaw6306.

[30] T. R. Dillingham, "Rehabilitation of the upper limb amputees," in *Rehabilitation of the Injured Combatant*, vol. 1. Washingtion, DC, USA: Office of the Surgeon General At TMM Publications, Department of the Army, 1998, ch. 3.

[31] E. Mastinu, P. Doguet, Y. Botquin, B. Håkansson, and M. Ortiz-Catalan, "Embedded system for prosthetic control using implanted neuromuscular interfaces accessed via an Osseointegrated implant," *IEEE Trans. Biomed. Circuits Syst.*, vol. 11, no. 4, pp. 867–877, Aug. 2017.

[32] E. L. Allwein, R. E. Schapire, and Y. Singer, "Reducing multiclass to binary: A unifying approach for margin classifiers," *J. Mach. Learn. Res.*, vol. 1, pp. 113–141, Sep. 2001.

[33] M. Ortiz-Catalan, R. Brånemark, and B. Håkansson, "BioPatRec: A modular research platform for the control of artificial limbs based on pattern recognition algorithms," *Sour. Code Biol. Med.*, vol. 8, p. 11, Apr. 2013.

[34] A. Calado, F. Soares, and D. Matos, "A review on commercially available anthropomorphic myoelectric prosthetic hands, pattern-recognition-based microcontrollers and sEMG sensors used for prosthetic control," in *Proc. IEEE Int. Conf. Auto. Robot Syst. Competitions (ICARSC)*, Apr. 2019, pp. 1–6.

[35] A. A. Adewuyi, L. J. Hargrove, and T. A. Kuiken, "An analysis of intrinsic and extrinsic hand muscle EMG for improved pattern recognition control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 4, pp. 485–494, Apr. 2015.

[36] M. Ortiz-Catalan, B. Håkansson, and R. Brånemark, "Real-time and simultaneous control of artificial limbs based on pattern recognition algorithms," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 756–764, Jul. 2014.

[37] M. A. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 8, pp. 1956–1965, Aug. 2008.

[38] G. Li, A. E. Schultz, and T. A. Kuiken, "Quantifying pattern recognition—Based myoelectric control of multifunctional transradial prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 2, pp. 185–192, Apr. 2010.

[39] A. Fougner, O. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. A. Parker, "Control of upper limb prostheses: Terminology and proportional myoelectric control—A review," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 20, no. 5, pp. 663–677, Sep. 2012.

[40] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–854, Jul. 2003.

[41] M. Powell, R. Kaliki, and N. Thakor, "User training for pattern recognition-based myoelectric prostheses: Improving phantom limb movement consistency and distinguishability," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 3, pp. 522–532, May 2014.

[42] L. Resnik, S. L. Klinger, and K. Etter, "The DEKA arm: Its features, functionality, and evolution during the veterans affairs study to optimize the DEKA arm," *Prosthetics Orthotics Int.*, vol. 38, no. 6, pp. 492–504, 2014.

[43] A. O. Perotto, *Anatomical Guide for the Electromyographer: The Limbs and Trunk*. Springfield, IL, USA: Charles C. Thomas, 1994.

[44] F. H. Netter, *Atlas of Human Anatomy* (Netter Basic Science). Elsevier-Health Sciences Division, 2018.

[45] A. H. Al-Timemy, G. Bugmann, J. Escudero, and N. Outram, "Classification of finger movements for the dexterous hand prosthesis control with surface electromyography," *IEEE J. Biomed. Health Informat.*, vol. 17, no. 3, pp. 608–618, May 2013.

[46] A. Al-Timemy, R. Khushaba, G. Bugmann, and J. Escudero, "Improving the performance against force variation of EMG controlled multifunctional upper-limb prostheses for transradial amputees," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 6, pp. 650–661, Jun. 2016.

[47] M. Ortiz-Catalan, E. Mastinu, P. Sassu, O. Aszmann, and R. Brånemark, "Self-contained neuromusculoskeletal arm prostheses," *New England J. Med.*, vol. 382, no. 18, pp. 1732–1738, Apr. 2020.

[48] F. S. Botros, A. Phinyomark, and E. J. Scheme, "Electromyography-based gesture recognition: Is it time to change focus from the forearm to the wrist?" *IEEE Trans. Ind. Informat.*, vol. 18, no. 1, pp. 174–184, Jan. 2022.

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