Real-Time and Simultaneous Control of Artificial Limbs Based on Pattern Recognition Algorithms

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***Abstract*—The prediction of simultaneous limb motions is a highly desirable feature for the control of artificial limbs. In this work, we investigate different classification strategies for individual and simultaneous movements based on pattern recognition of myoelectric signals. Our results suggest that any classifier can be potentially employed in the prediction of simultaneous movements if arranged in a distributed topology. On the other hand, classifiers inherently capable of simultaneous predictions, such as the multi-layer perceptron (MLP), were found to be more cost effective, as they can be successfully employed in their simplest form. In the prediction of individual movements, the one-vs-one (OVO) topology was found to improve classification accuracy across different classifiers and it was therefore used to benchmark the benefits of simultaneous control. As opposed to previous work reporting only offline accuracy, the classification performance and the resulting controllability are evaluated in real time using the motion test and target achievement control (TAC) test, respectively. We propose a simultaneous classification strategy based on MLP that outperformed a top classifier for individual movements (LDA-OVO), thus improving the state-of-the-art classification approach. Furthermore, all the presented classification strategies and data collected in this study are freely available in BioPatRec, an open source platform for the development of advanced prosthetic control strategies.**

***Index Terms*—Artificial limbs, artificial neural networks (ANN), mixed classes pattern recognition, prosthetic limbs, simultaneous pattern recognition.**

I. Introduction

The state-of-the-art technology for the rehabilitation of amputees in clinics around the world is commonly a dual-site controlled myoelectric prosthesis. This device is controlled using a simple threshold detection method for the activation of one output (e.g., hand close) following one input, which is the myoelectric signals (MES) of a group of muscles (e.g., wrist flexors). Antagonistic muscles are therefore normally required to control one degree of freedom. In the case of a multifunctional prosthesis with several degrees of freedom (DoF), but still having only two control signals, the switching between DoF or predefined grasps is normally made by cocontraction as in a finite-state machine. This serial operation is slow and unnatural, in addition to requiring considerable training and cognitive effort. It is reasonable to argue that the limited functionality provided by this technology is one of the reasons for its unpopularity. In spite of the fact that a fully motorized arm (elbow, wrist and hand) could be fitted today in patients using off-the-shelf prosthetic components, this is rarely done.

In order to achieve simultaneous control using the direct mapping strategy, it would be enough to assign the MES of each muscle to its respective limb motion. However, this is practically impossible for several reasons, i.e., considerable myoelectric interference (crosstalk) is commonly found on superficial recordings and, inherently to an amputation, muscles are lost and so are the myoelectric control sites.

The simultaneous control of two DoF using a direct scheme has been demonstrated by Kuiken *et al.* [1] in patients with targeted muscle reinnvervation (TMR). This was achieved thanks to the TMR procedure which increases the number of independent control sites [2]. Unfortunately, even in TMR patients, it is not always possible to satisfactorily isolate MES in surface recordings, thereby admittedly making pattern recognition schemes desirable [2], [3].

An alternative to the direct control scheme is the use of pattern recognition algorithms (classifiers) which map several inputs (mixed MES from different muscles) to several outputs (limb motions). Although this approach is potentially capable of providing simultaneous control, most prosthetic research has focused on predicting individual motions which limits the control to a serial operation (a single motion at a time). A detailed review of prosthetic control has been provided by Scheme and Englehart [4].

In 1973, Herberts *et al.* reported the simultaneous control of three DoF using pattern recognition, however, the simultaneous performance was not evaluated [5]. More recently, Yatsenko *et al.* used an array of surface electrodes for the simultaneous classification of three DoF with offline accuracies up to 75% [6]. The algorithm employed principal component analysis, whitening, and orthonormalization of the feature vectors assuming linear relationships in the mixed MES. Based on the same principle, Jiang *et al.* used a biologically inspired algorithm applying nonnegative matrix factorization (NMF) [7]. This method was tested for wrist movements predicting two of three DoF. In addition, it was compared with a multi-layer perceptron (MLP) which showed slightly yet consistently better performance. It was argued that this was due to the capability of MLP to handle nonlinear relationships by Muceli *et al.*, who

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also used several MLPs in a distributed topology for the prediction of hand kinematics including hand close as an additional movement [8]. The prediction of wrist kinematics was later studied by Jiang *et al.*, following the idea of modifying the standard single classifier topology to use dedicated MLPs [9].

In this study, we investigated different classifiers and their distribution in a variety of topologies that enable simultaneous predictions. As opposed to previous work, where the prediction accuracy was only measured using prerecorded data (offline), the performance of the classification strategies suggested here was also evaluated using the real-time metrics provided by the Motion Test [2]. Different research groups have shown that offline accuracy does not necessarily correspond to real-time performance [10]–[12], to the point at which classifiers with similar offline accuracy can have different real-time results [13]. Furthermore, controllability under a simultaneous scheme, which is different from measuring real-time classification as done by the Motion Test, was also evaluated. The target achievement control (TAC) test was employed as a quantitative evaluation of controllability [14].

One additional difference compared with previous work predicting kinematics is that these strategies were designed for unilateral amputees and require additional hardware such as motion capture systems [8], [9] and force transducers [7]. Conversely, only surface EMG is required in the strategies presented here, thus making them equally valid for unilateral or bilateral amputees. This also results in a simplified setup that is more suitable for clinical application.

Different classifiers have previously been compared in the offline prediction of individual movements using surface EMG [12], [15], as well as in real-time [13]. We extended this work to include additional classifiers and benchmarking their performance in different topologies. This was then used as a baseline for comparing the proposed simultaneous strategy. The ultimate aim of this work is to investigate the suitability and advantages of simultaneous over serial control strategies based on myoelectric pattern recognition.

Conducting scientific research calls for repeatability. Unfortunately, this is rarely done in prosthetic control research due to the considerable number of variables involved in studies related to pattern recognition, which makes true comparisons practically impossible. As an initiative for a common data repository and benchmarking platform, the data and source code from this work are freely available in the second release of BioPatRec (TVÅ). BioPatRec is an open source platform for the development of advanced prosthetic control strategies based on pattern recognition algorithms [13].

II. Methods

The studies comprising this work are summarized in Table I. The following method's description applies to all the studies unless explicitly stated.

TABLE I
SUMMARY OF STUDIES

Aim	Evaluation	Ind. / Sim.	Mov.	Sub.
Discrim. Offline	Offline Acc.	Ind.	11	20
Discrim. Offline	Offline Acc.	Sim.	27	17
Discrim. Real-time	Motion Test	Sim.	27	10
Controllability	TAC Test	Ind. & Sim.	27	6

All subjects participating in this study were able-bodies. Ind. = individual, Sim. = simultaneous, Mov. = movements, Sub. = subjects, and Discrim. = discrimination.

A. Classifiers and Classifier Topologies

There is a wide variety of fundamentally different pattern recognition algorithms, and although some of them are inherently capable of simultaneous classification (e.g., MLP), others are limited by their design to produce a single output (e.g., linear discriminant analysis). A mixture of these classifiers was evaluated in this work: Linear Discriminant Analysis (LDA) as a statistical classifier part of discriminant analysis [16]; Multi-Layer Perceptron (MLP) as a supervised Artificial Neural Network (ANN) [17]; Self-Organized Map (SOM) as an unsupervised ANN [17]; and Regulatory Feedback Networks (RFN) as a new paradigm in classification based on negative feedback rather than learning [13].

Although some of these algorithms compute the most likely pattern/class (C) by majority voting (single output), they can be split into different topologies using dedicated classifiers (K), thus enabling simultaneous predictions (mixed outputs). One way of achieving mixed outputs is the creation of several binary classifiers, which is known as problem transformation by *binary relevance* [18], [19]. The following topologies (transformations) were used in this study.

1) *Single:* This is the simplest and most commonly used topology, where all inputs feed a single classifier which is trained to discriminate all labels. In order to be used for simultaneous predictions, the classifier is also fed with information relating to the mixed classes during the training/learning process. Although the number of outputs (O) remained the same as that of the individual classes (C_{ind}), simultaneous prediction is possible because more than one output can be activated in parallel. It is formed by $K = 1$ classifiers with $O = C_{\mathrm{ind}}$.
2) *All Movements as Individual (AMI):* Similar to a single classifier but applies the *label power set* problem transformation method [19], which means creating a new label for each mixed movement. The number of outputs is therefore expanded to the total number of classes (C_{all}). In this case, only one output is activated at a time. It is formed by $K = 1$ classifiers with $O = C_{\mathrm{all}}$.
3) *Ago/Antagonist-Mixed (AAM):* This topology assumes that the motions are paired in ago/antagonist movements (essentially a DoF). There are as many classifiers as DoF and each classifier is fed with the feature vectors of at least three classes; two of them are the movements related to the DoF, and the third is a mixed class combining all the other movements. A fourth class is optional if the *rest* class (no motion) is available. The output vector contains the winner motion from each classifier, $O = C_{\mathrm{ind}}$. It is formed by $K = 2/(C - 1)$ classifiers, considering that there is a *rest* class.
4) *One-Vs-All (OVA):* In this topology, each classifier is trained to discriminate between one class and a mixed class containing all the others. LDA in OVA has been used

Fig. 1. Illustration of a subject performing the TAC test. Target posture shown by the shadow hand was supination, while the solid hand is controlled by the subject. Location of eight bipolar surface electrodes around the most proximal third of the forearm can be observed. Videos comparing individual and simultaneous control are available at the BioPatRec project online site [23].

successfully by Hargrove *et al.* to predict individual motions [20]. This topology enables any pattern recognition algorithm to predict simultaneously different classes, as the output vector contains the winner of each classifier. It is formed by $K = C$ classifiers with $O = C_{\text{ind}}$.

5) *One-Vs-One (OVO):* An individual classifier is trained in this topology to discriminate between two motions. The output is computed by majority voting and therefore it can only be one winning class. This approach has been shown to be superior to a single classifier predicting individual motions by Scheme *et al.* [12]. It is formed by $K = C \times (C-1)/2$ classifiers with $O = C_{\text{ind}}$.
6) *All-And-One (AAO):* It has been observed that a common misclassification by the OVA strategy was that the correct class was actually the second best ranked. In order to solve this problem, Gracía-Pedrajas and Ortiz-Boyer [21] proposed the AAO strategy where the OVA top two ranked classes competed again in OVO. It is formed by $K = C^2/2$ classifiers with $O = C_{\text{ind}}$.

In order to improve stability during real-time predictions, the output of any topology was considered as the *rest* class if the *average mean absolute* value of all channels was lower than the *rest* periods during the recording session (noise floor).

B. Signal Acquisition and Processing

The recording protocol and hardware were described previously for individual [13] and simultaneous [22] movements. Briefly, disposable Ag/AgCl electrodes (diameter = 1 cm) in bipolar configurations (2 cm interelectrode distance, one distal and one proximal) were used to record surface MES around the most proximal third portion part of the forearm. The first pair (channel 1) was consistently placed along the extensor carpi ulnaris and the rest equally spaced following the lateral direction around the forearm (Fig. 1). The subjects were instructed by BioPatRec to execute and maintain the different movements for 3 s and relax for the same amount of time, three times. A virtual hand timely demonstrated the requested motions to facilitate the task for the user, which could be otherwise confusing during simultaneous motions. Additionally and in order to prepare the subject for each motion, an initial "dummy" execution was requested as demonstrative example from which no signals were recorded. Fifteen percent of the contraction time was discarded at the beginning and end of the recording, normally conserving information on the dynamic portion of the contraction, as subjects do not immediately contract after requested [13]. The remaining data was used in time windows of 200 ms with a 50 ms time increment, from which four time features were extracted (mean absolute value, zero crossings, slope sign changes, and wave length).

The number of movements for the individual classification study was 11 (hand open/close, wrist flexion/extension, pro/supination, side grip, fine grip, agree or thumb up, pointer or index extension, and *rest*), recorded by four equally spaced bipolar electrodes [13]. The movements involved in the simultaneous study were hand open/close, wrist flexion/extension and pro/supination, plus all their possible combinations—that is three DoF with six individual and 20 mixed motions for a total of 27 classes (considering the *rest* class) recorded using eight bipolar electrodes. These movements were selected because they are currently feasible using commercially available prosthetic devices. A recording session for simultaneous movements lasted 10.4 min, and information from all classes was used to train the classifiers.

The recorded MES and related acquisition and subject information is freely available as part of the bioelectric signals repository of BioPatRec. They can be found in BioPatRec under the labels *10mov4chForearmUntergeted* and *6mov8chFUS* for the individual (20 subjects—11 classes) and simultaneous (17 subjects—27 classes) sessions, respectively.

All the experiments were approved by the Swedish Regional Ethics Committee in Gothenburg (626-10, T688-12).

C. Offline and Real-Time Evaluations

The offline evaluations were performed by dividing the available data into three sets: training (40%), validation (20%) and testing (40%). The feature vectors were randomized into the different sets, and the offline accuracy was measured using the testing set only. This was repeated ten times (crossvalidation) to produce an average offline performance for each subject.

The Motion and TAC tests were originally developed at the Rehabilitation Institute of Chicago [2], [14], and their implementation in BioPatRec is described in [13]. The Motion Test was used to evaluate real-time classification, whereas the TAC test was used to evaluate the resulting controllability. Videos demonstrating these tests are available on BioPatRec's project site [23]. Both tests consisted of two trials of three repetitions of each movement randomly requested. New predictions were made every 50 ms.

The Motion Test required 20 correct predictions within 10 s to consider a motion completed. The time between the first prediction different from *rest* and the 20th correct prediction is reported as the completion time. The number of completed motions over the total number of motions attempted is reported as the completion rate. The real-time accuracy was calculated using the predictions during the completion time, and only completed motions contributed [13].

The TAC test required the artificial limb to be placed within ± 5 degrees of the target posture and a two-second dwell time to consider a motion achieved. The timeout was 20 s, 25 s, and 30 s, for one (individual), two, and three mixed movements, respectively. The artificial limb was free to move in any direction dictated by the prediction strategy, which meant that any misclassification effectively caused it to deviate from its aimed target posture. The target postures were 40 degrees away from the neutral position, leaving scope for overshooting, thus requiring the user to compensate with antagonistic motions in that case. As opposed to the original version by Simon *et al.* [14], the virtual hand was placed in the neutral position before attempting to reach the target posture. This was done to facilitate testing the mixed movements under the same circumstances. The path efficiency was computed by the ratio between the shortest path from the neutral to the target posture, over the actual path under the subject's control.

Additionally to use only the raw prediction from the classification topologies, the best known postprocessing strategy (velocity ramp [24]) was also employed for the TAC test. This decision-based open-loop algorithm is equally applicable for individual and simultaneous classifiers. The maximum displacement allowed was two degrees per prediction, with new predictions every 50 ms, the maximum speed was 40 degrees per second. The ramp length used was 10 with a down count of 2. A subject performing the test is shown in Fig. 1.

When comparing different classifiers in the Motion and TAC tests, the order of execution was randomized between subjects to avoid favoring one through the learning effect. Moreover, the tests were conducted at the same session to avoid differences in electrode placement and performance during the recording session.

Statistical significance was measured using the Wilcoxon Signed-Rank test, which has been shown to be appropriate for comparing different classifiers in common data sets [25]. Statistical significance was considered at $\mathrm{p} < 0.05$.

III. Results

The results are presented in box plots where the central line represents the median value; the edges of the box are the 25th and 75th percentiles; the whiskers give the range of data values without outliers ($\sim \pm 2.7\sigma$); solid markers represent the mean values.

A. *Offline Individual (Single Classes)*

The results for individual movements (11 classes, 20 subjects) are summarized in Table II, and the offline accuracy is plotted in Fig. 2. The creation of dedicated classifiers, and the redistribution of input information characterizing the system, impact not only the classification accuracy but also the training and prediction speed (due to convergence and output computation, respectably). Since the absolute speed values are highly dependent on the processing hardware, it is of greater interest to evaluate the increments in comparison to the single topology. As a reference, the time required for predicting all the testing sets (49×11) was 0.8 ms, 0.07 ms, 0.6 ms, and 1.1 ms for single LDA, MLP, SOM, and RFN, respectively.

B. *Offline Simultaneous (Mixed Classes)*

The results for simultaneous movements (27 classes, 17 subjects) are summarized in Table III, and the offline accuracy is plotted in Fig. 3. As for the individual movements, the effect on training and testing speed is reported against the single topology. Not surprisingly, the LDA classifier had low average prediction accuracy, since it is inherently incapable of simultaneous predictions in the single topology.

TABLE II
Offline Results for Individual Movements

	Offline Accuracy (%)			
	Single	**OVO**	**OVA**	**AAO**
LDA	92.2 (3.8σ)	**95.7 (2.6σ)**	50.6 (13.5σ)	94.0 (2.4σ)
MLP	90.0 (6.2σ)	**92.8 (4.3σ)**	86.6 (7.7σ)	**92.8 (4.4σ)**
SOM	93.6 (3.4σ)	**94.5 (3.1σ)**	92.1 (4.3σ)	93.4 (3.5σ)
RFN	83.7 (8.9σ)	**86.9 (5.0σ)**	12.0 (11.5σ)	68.0 (25.0σ)
	Training Time Increment			
LDA	1	1.8 (0.05σ)	2.5 (0.07 σ)	**3.5 (0.1 σ)**
MLP	1	11.6 (2.0 σ)	8.8 (1.5 σ)	**19.6 (3.0 σ)**
SOM	1	3.4 (0.4 σ)	10.0 (2.9 σ)	**17.0 (4.5 σ)**
RFN	1	5.1 (0.6 σ)	5.1 (0.5 σ)	**9.7 (0.8 σ)**
	Testing Time Increment			
LDA	1	**3.1 (0.05 σ)**	0.7 (0.02 σ)	0.7 (0.01 σ)
MLP	1	**40.5 (0.1 σ)**	8.7 (0.03 σ)	9.6 (0.03 σ)
SOM	1	**16.8 (0.9 σ)**	5.7 (1.1 σ)	6.8 (1.1 σ)
RFN	1	**28.4 (4.4 σ)**	6.5 (0.8 σ)	7.4 (0.8 σ)

Results of the offline pattern recognition of 10 individual movements plus *rest*, in 20 subjects. The highest accuracy values per classifier are highlighted in bold. See Fig. 2 for a graphic display and statistical significance. The increment in training and testing time is in relation to the single topology.

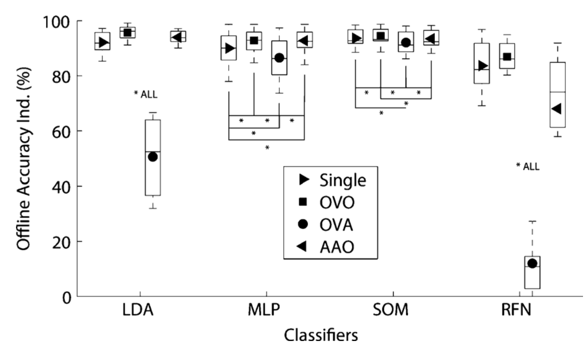

Fig. 2. Offline prediction accuracy of 11 individual classes in 20 subjects. Statistical significance is shown by "*". All classifiers had a statistically different accuracy compared with one another in the Single, OVO and OVA topologies. In the AAO topology, only LDA-MLP, LDA-SOM, and MLP-SOM failed to reach statistical significance.

C. *Motion Test Results*

The Motion Test for simultaneous movements was performed by ten subjects using the MLP classifier in Single, OVA, and AAM topologies in order to investigate whether differences in real-time prediction exist despite their practically identical offline accuracy (Table III). These results are summarized in Table IV and illustrated in Fig. 4. The cumulative completion rate is presented in Fig. 5 as a graphic indicator of overall completion performance versus time. Preliminary results in six subjects have been previously reported [22].

No difference was found between the Single and AMM topologies when subjects were asked about their perceived performance. Conversely, they all reported that OVA was the least stable, which is in line with its poor performance on this test.

TABLE III
OFFLINE RESULTS FOR SIMULTANEOUS MOVEMENTS

	Offline Accuracy (%)			
	Single	**OVA**	**AAM**	**AMI**
LDA	25.7 (44.3σ)	75.1 (9.9σ)	79.0 (7.9σ)	**93.7 (2.5σ)**
MLP	93.5 (2.8σ)	93.2 (2.5σ)	93.5 (3.0σ)	**94.2 (2.7σ)**
SOM	**93.8 (3.4σ)**	93.2 (3.2σ)	93.7 (3.4σ)	92.2 (3.8σ)
RFN	17.8 (33.0σ)	22.4 (16.3σ)	34.0 (20.4σ)	**82.3 (8.4σ)**
	Training Time Increment			
LDA	1	**5.2 (0.1 σ)**	2.6 (0.05 σ)	2.1 (0.04 σ)
MLP	1	**6.8 (3.4 σ)**	2.9 (0.5 σ)	3.0 (2.1 σ)
SOM	1	**4.6 (0.2 σ)**	1.8 (0.08 σ)	0.7 (0.03 σ)
RFN	1	**3.6 (0.2 σ)**	2.2 (0.04 σ)	1.8 (0.03 σ)
	Testing Time Increment			
LDA	1	1.1 (0.02 σ)	1.3 (0.03 σ)	**14.0 (0.3 σ)**
MLP	1	**5.9 (0.02 σ)**	3.3 (0.01 σ)	1.0 (.002 σ)
SOM	1	**3.8 (0.14 σ)**	1.8 (0.04 σ)	1.4 (0.02 σ)
RFN	1	**4.9 (0.26 σ)**	2.9 (0.08 σ)	1.2 (0.03 σ)

Average results from 17 subjects for the offline prediction of six individual and 20 mixed movements, plus *rest*. The highest values are highlighted in bold per classifier. See Fig. 3 for a graphic display and statistical significance.

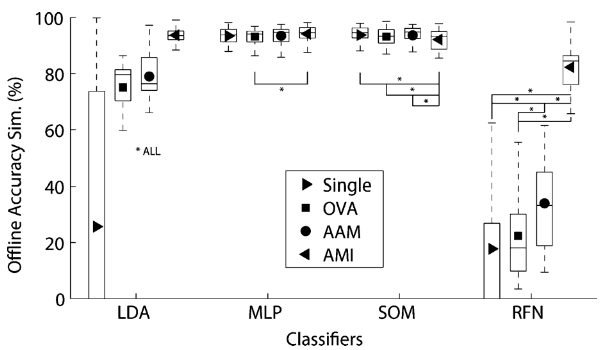

Fig. 3. Offline prediction accuracy of 27 classes (7 individual and 20 mixed) in 17 subjects. Statistical significance is shown by "*". All classifiers had a statistically different accuracy compared with one another between topologies apart from MLP-SOM in Single, OVA, AAM, and LDA-MLP in AMI.

TABLE IV
MOTION TEST—SIMULTANEOUS MOVEMENTS

	Mixed Movements			
	1 (Ind.)	**2**	**3**	**AVG**
	Real-time Accuracy (%)			
Single	52.1 (7.0σ)	51.9 (5.5σ)	52.7 (5.2σ)	52.2 (5.6σ)
OVA	51.9 (11.8σ)	50.9 (6.8σ)	58.1 (6.4σ)	53.2 (8.4σ)
AAM	**54.9 (9.1σ)**	**53.8 (5.4σ)**	**56.6 (5.5σ)**	**54.8 (6.3σ)**
	Completion Time (seconds)			
Single	**2.9 (0.5σ)**	**2.7 (0.3σ)**	2.6 (0.5σ)	**2.7 (0.4σ)**
OVA	3.4 (1.0σ)	2.9 (0.6σ)	**2.4 (0.4σ)**	2.9 (0.7σ)
AAM	**2.9 (0.8σ)**	**2.7 (0.3σ)**	**2.4 (0.4σ)**	**2.7 (0.5σ)**
	Completion Rate (%)			
Single	**88.9 (6.8σ)**	**93.1 (4.3σ)**	92.5 (4.6σ)	**91.9 (5.1σ)**
OVA	81.7 (10.4σ)	91.1 (7.8σ)	94.0 (5.2σ)	89.8 (8.9σ)
AAM	76.9 (12.5σ)	91.1 (7.2σ)	**94.6 (4.3σ)**	88.9 (10.3σ)

Average results from 10 subjects performing simultaneous movements in three DoF. These were six individual, 12 with two mixed movements, and eight with three mixed movements. See Fig. 4 for a graphic display and statistical significance.

D. TAC Test Results

The TAC test was performed by six subjects using the raw individual and simultaneous classification, as well as including

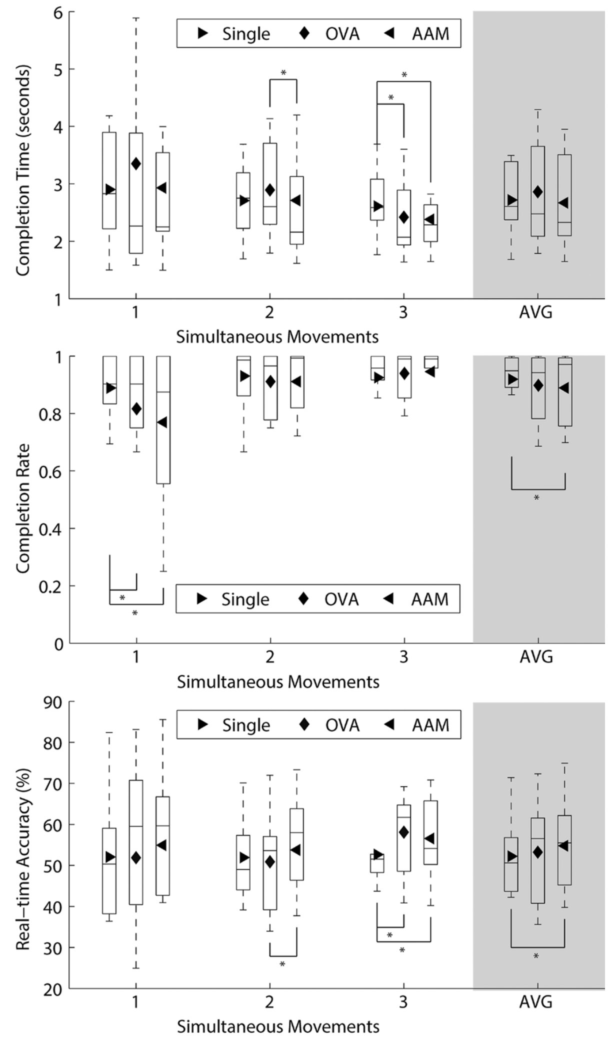

Fig. 4. Motion Test results from ten subjects performing simultaneous motions in three DoF (6 individual and 20 mixed classes). Statistical significance is shown by "*". Results are divided by the number of mixed (combined) movements.

postprocessing (velocity ramp). The LDA classifier in OVO topology was used as the base for comparing controllability. We have previously found that LDA outperforms other classifiers, including MLP, on the real-time prediction of individual motions [13]. Additionally, the offline results (Table II) suggest that LDA can be further improved when built in the OVO topology, as also shown by others [12], thus making it one of the best performing algorithms for individual predictions. On the other hand, the Single topology for MLP was chosen as the simultaneous strategy because of its simplicity and since no considerable difference was found compared with AAM. These results are summarized in Table V and graphically represented in Fig. 6. As in the case of the motion test, the cumulative completion rate was also computed and is shown in Fig. 7.

IV. DISCUSSION

A. Classifiers and Topologies

It has been shown that individual motions can be successfully predicted offline using a variety of pattern recognition al-

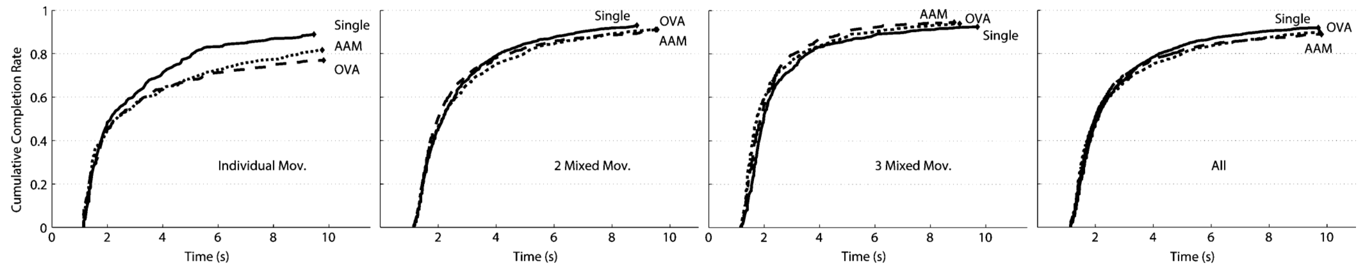

Fig. 5. Cumulative completion rate (Motion Test) from ten subjects performing simultaneous motions in 3 DoF (6 individual and 20 mixed classes).

TABLE V
TAC TEST—INDIVIDUAL VERSUS SIMULTANEOUS CONTROL

MM	LDA	LDA Ramp	MLP	MLP Ramp
		Path Efficiency (%)		
1	73.6 (28.3σ)	**93.5 (13.9σ)**	66.5 (29.2σ)	83.7 (24.1σ)
2	45.8 (15.5σ)	61.2 (9.9σ)	54.9 (26.8σ)	**70.6 (24.6σ)**
3	36.0 (11.1σ)	47.4 (7.1σ)	55.8 (25.2σ)	**68.2 (21.0σ)**
AVG	50.3 (23.6σ)	65.0 (20.0σ)	57.9 (27.3σ)	**73.0 (24.2σ)**
		Completion Time (seconds)		
1	4.0 (3.2σ)	**3.0 (1.9σ)**	4.5 (3.2σ)	4.1 (2.8σ)
2	7.7 (3.9σ)	8.0 (3.9σ)	6.8 (4.8σ)	**6.6 (4.7σ)**
3	12.0 (5.7σ)	12.5 (4.6σ)	**7.3 (5.2σ)**	7.7 (4.8σ)
AVG	7.9 (5.2σ)	8.1 (5.1σ)	**6.4 (4.7σ)**	**6.4 (4.5σ)**
		Completion Rate (%)		
1	92.1 (14.6σ)	98.1 (6.6σ)	91.2 (20.1σ)	**99.5 (2.8σ)**
2	84.5 (26.9σ)	95.1 (12.0σ)	91.0 (17.5σ)	**96.3 (9.8σ)**
3	73.3 (33.1σ)	87.2 (26.5σ)	93.1 (12.3σ)	**97.6 (6.9σ)**
AVG	82.8 (27.6σ)	93.4 (17.5σ)	91.7 (16.7σ)	**97.4 (7.8σ)**

TAC test average results for six individual and 20 mixed movements (MM) in six subjects. See Fig. 5 for a graphic display and statistical significance.

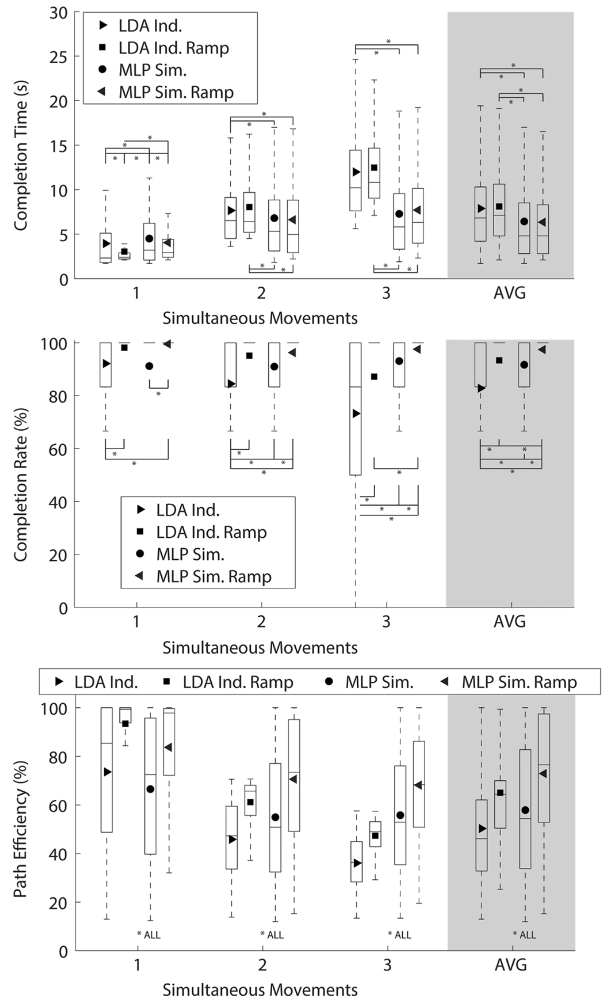

Fig. 6. TAC test results. Simultaneous + ramp strategy obtains the best overall performance on all three indicators. Use of the velocity ramp did not significantly affect the completion time for mixed movements, but it reduced it for individual targets, as expected. On the other hand, it consistently improved path efficiency.

gorithms [12], [13], [15]. Our results suggest that this can be further improved across classifiers by distributing the task in the OVO topology, which comes at the cost of higher memory requirements and longer training and prediction times. However, since all the strategies have prediction times short enough to be used for real-time control (<50 μs per classification), it can be argued that applying this topology has no practical cost. It is worth mentioning that, since the output of OVO is computed by majority voting, it can only be used for the prediction of individual movements. However, if the output computation is modified to use thresholds instead, it could potentially be used for simultaneous predictions as well.

Our results demonstrate that virtually any classifier can be used for the prediction of simultaneous movements, if arranged in a distributed topology. There are some clear advantages when it comes to choosing an algorithm that is inherently capable of such a task. For instance, no modifications are required for a single MLP to classify individual or simultaneous movements, apart from the information that is fed during training. Conversely, a classifier based on majority voting, such as LDA, only showed acceptable results in the AMI topology which, despite not being the most elegant solution, was found capable of handling three DoF simultaneously. It is important to remember that in this topology, as the number of DoF increases, the classes and computational requirements grow exponentially, thus compromising the scalability of this "brute force" approach. This was the reason why it was not pursued further in this work. The cost of the AAM topology, however, is considerably lower and it might still be worth exploring for some classifiers. In any case, it can be argued that any classifier could be used in this task if optimally implemented, and therefore the experience of the practitioner with a given classifier might be an even more important factor than the algorithm itself.

The recording session for the simultaneous control of 3 DoF, as done in this work, required 10.4 min. We have previously shown that the same recording session can be reduced 50% in

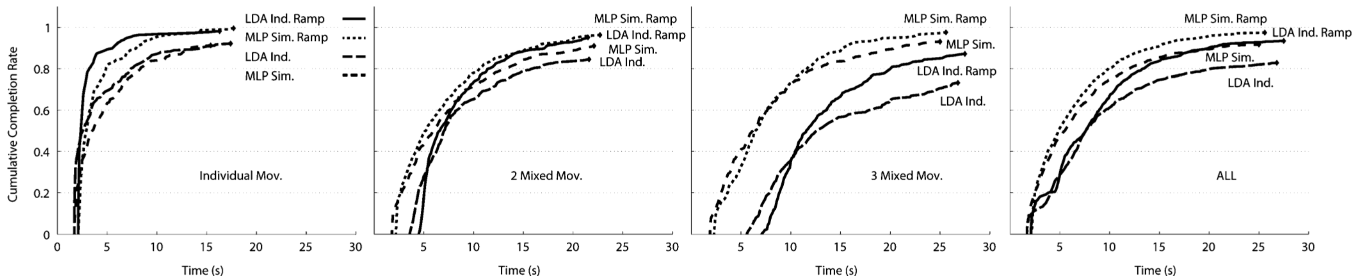

Fig. 7. TAC test cumulative completion rate. MLP classifier with velocity ramp shows the best performance in mixed movements. Individual movements were executed more rapidly using the LDA-OVA classifier with velocity ramp.

length, without a considerable impact in the prediction of individual movements [13]. Similarly, if only half of the training and validation sets are used to feed the single MLP in the presented simultaneous prediction task, the offline accuracy falls only 1.8%, from 93.5% $(2.8\%\sigma)$ to 91.7% $(3.2\%\sigma)$. The effect of such reduction still needs to be tested in real-time in order to truly evaluate its impact. Additionally, the practical implication of training times of few minutes when using standalone systems also remains to be investigated.

B. *Real-Time Classification of Simultaneous Motions*

We have previously found that classifiers with similar offline accuracy can produce different real-time classification [13]. This made it necessary to investigate whether an algorithm which is inherently capable of simultaneous predictions (MLP) can have different real-time performance depending on the topology that is employed. Our results suggest that the difference in real-time prediction is marginal in this case. It should be noted that real-time evaluation adds the human factor as a new source of error and noise. The motivation and concentration of the subject can vary during the test, thus making small differences between classifiers imperceptible. On the other hand, it could be argued that if these differences are so small that they cannot be discerned, they are probably insignificant in practice. Once postprocessing or control algorithms are introduced into the control strategy, small differences in classification performance will potentially disappear.

One necessary consideration when proposing any new improvement is that it should not sacrifice the benefits already achieved. In this case, this would be the controllability of individual motions. Conflicting results were found between the Single and AMM topologies in this respect. The AAM showed better prediction accuracy, while the Single topology had a higher completion rate. This difference can be explained by the fact that the prediction accuracy is only computed using the completed motions and therefore the more motions completed with long completion times would negatively affect it. In any case, the resulting controllability measured in the TAC test was still poorer than the individual controller (LDA-OVO). During this work, it was observed that false positives were the main problem for MLP during individual predictions, and that by adjusting the output thresholds, this could be considerably improved [26]. Further experiments are currently being performed to investigate whether this modification to the classification strategy truly results in equal or better controllability than LDA-OVO for individual movements.

C. *Resulting Controllability Using Simultaneous Predictions*

As hypothesized, the controllability for mixed movements was increased when using simultaneous predictions. The MLP without postprocessing showed similar results to the LDA-OVO when using it, and once the postprocessing was added to the MLP, consistent improvements were found, thus demonstrating that the presented simultaneous strategy improves the state of the art in classification approaches.

It is worth noting that the higher path efficiencies were achieved on individual movements, which are also the easiest task in the test. There is a certain degree of difficulty in the test itself when increasing the number of DoF that must be considered. Estimating and visualizing the final position might be cumbersome, thus partially accounting for missing the perfect path, in spite of the fact that the control strategy could actually be performing as the subject intended. Some of these complications can be observed in the video examples available on the project site [23].

It is reasonable to expect that the controllability of individual motions is the most relevant at the final stage of actuation, i.e., grasping or releasing. Conversely, simultaneous motions appear to be clearly advantageous when positioning the prosthesis. As mentioned before, improvements have been devised to increase the controllability of individual motions to equal that of the best individual controllers. The real practical implications, however, still need to be evaluated in standalone implementations where patients are allowed to use it in their daily activities.

D. *Repeatability in Prosthetic Control Research*

The subjects' skills, experience, and motivation during the testing tasks are difficult to quantify and therefore compensate when benchmarking results from different studies. Additionally, there are other study-dependent variables that can considerably change the absolute real-time results, such as the electrode type, number, and placement; acquisition and processing electronics; and, signal processing, feature extraction, and classifier training methods. For this reason, absolute real-time results should not be used directly to compare different studies, instead the relative improvements over a base strategy that was tested on the same subjects, and under the same circumstances, should be used. Conversely, in offline evaluations the same data can be used to mitigate the mentioned sources of variability and provide a more reliable comparison between different algorithms. In an effort to improve repeatability and foster further development, the source code and data gathered during this work are freely available in the second release of BioPatRec [13].

V. Conclusion

The use of pattern recognition-based controllers has been clinically limited due to a number of practical problems mainly attributed to surface recordings. This problem is currently being addressed using different, but not always mutually exclusive, approaches such as conforming dry surface electrodes, TMR, and in our case, implanted neuromuscular interfaces permanently communicated through an osseointegrated implant. In any case, if these controllers are to be used, this work suggests that simultaneous control must be considered, as it increases the overall controllability without a considerable increment in complexity. Furthermore, simultaneous control is a required feature for a more natural control of artificial limbs.

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