**Real-time classification of simultaneous hand and wrist motions using Artificial Neural Networks with variable threshold outputs**



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# Real-Time Classification of Simultaneous Hand and Wrist Motions Using Artificial Neural Networks with Variable Threshold Outputs

Max Ortiz-Catalan, Bo Håkansson, and Rickard Brånemark

***Abstract*—**Limb motions normally involve more than one degree of freedom combined in a coordinated manner. Although prosthetic hardware today could be combined for a highly motorized limb replacement, the control options available to amputees are so limited that this approach is rarely used. In this work, we introduce a classification strategy for the real-time simultaneous prediction of the individual movements present in natural motions. The real-time evaluation of this strategy based on a Multi-Layer Perceptron (MLP) with variable threshold outputs resulted in high motion completion rates. Moreover, the MLP alone showed higher offline accuracy than previously reported. This classifier was developed and evaluated in BioPatRec, an open source framework for advanced prosthetic control strategies based in pattern recognition algorithms. The source code and the data obtained in this study are freely available to be used for further algorithms development and benchmarking.

***Keywords*—**Artificial Neural Networks, Electromyography, Mixed-label, Mixed-class, Simultaneous Prosthetic Control.

## I. Introduction

MYOELECTRIC signals (MES) produced during muscle contraction contain valuable information about their resulting motions. In the case of amputees, the reaming muscles in the stump can still produce MES useful for the prediction of motion intent [1]. As an effort to advance limb prosthetics, several pattern recognition algorithms have been used to predict limb movements by decoding associated surface MES [1–7]. The majority of this work, however, has been focused on the prediction of individual movements. Unfortunately, since only one movement is predicated at the time, this scheme is restraint to the serial control of different degrees of freedom (DoF), which is cumbersome, slow, and unnatural. On this study, an artificial neural network (ANN) with variable thresholds outputs is proposed as a solution for the simultaneous prediction of the different motions involved in more natural and complex movements.

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The presented pattern recognition task can be named in different ways: multi-class, multi-label, mixed-label, etc… Multi-label classification problems are normally formulated by having a feature set bellowing to each of the different labels [8], e.g. a scientific article is associated to different keywords (labels). Analogously, a movement involving different DoF would have the associated labels of each DoF. A difference in this case however, is that the feature vectors are also mixed, and therefore the terminology of mixed-label is here more appropriated. A mixed-label problem also implies that at least two classes are involved, and therefore its multi-class nature can be deduced.

The feasibility of decoding simultaneous motions has been shown by Yatsenko *et al.* with offline accuracies up to 75% using a grid of 22 electrodes [9]. Their algorithm employed principal component analysis (PCA), whitening, and orthonormalization of the feature vectors assuming linear relationships in the combined MES. Based on the same principle, Jiang *et al.* proposed the biologically inspired Nonnegative Matrix Factorization (NMF) algorithm [10]. The NMF was tested for wrist movements satisfactorily predicting 2 out of 3 DoF. Additionally, it was compared to a multi-layer perceptron (MLP), which showed slightly but consistently better performance. This was argued to be due to the MLP capabilities to handle non-linear relationships by Muceli *et al.*, who also used MLP for the prediction of hand kinematics including “hand close” as an additional movement [11].

In this study, the “hand open” and “hand close” movements are included together with 4 wrist motions for a total of 3 DoF. Additionally, the classification strategy presented in this work only use surface MES as oppose to the previous work where additional hardware such as motion capture systems [11], [12], and force transducers [10] are required. Systems using motion capture hardware are mainly designed for unilateral amputees, where the contralateral limb is still available. Conversely, the strategy here presented is suitable for both; unilateral and bilateral amputees.

Previous classifiers for simultaneous movements have been evaluated using pre-recorded data only (offline). Contrary to common sense, it has been shown that offline accuracy does not necessarily reflects real-time performance [1], [6], [7], [13]. This work is the first to evaluate the real-time performance of a simultaneous limb motion classifier.

This study was approved by the Swedish Regional Ethics

Committee in Gothenburg (626-10, T688-12).

## II. Methods

### A. Signal Acquisition and Processing

Eight pairs of disposable Ag/AgCl electrodes (Ø = 1 cm) in a bipolar configuration (2 cm inter-electrode distance) were placed equally distributed around the proximal third of the forearm; one distal and one proximal. The first pair (channel 1) was consistently placed along the extensor carpi ulnaris and the rest following the lateral direction around the forearm. The bioelectric amplifier was an in-house design (MyoAmpF2F4-VGI8) with 66 dB gain, and embedded active filtering: 4th order high-pass filter at 20 Hz; 2nd order low-pass filter at 400 Hz; and, Notch filter at 50 Hz. The signals were digitalized at 2 kHz with 16-bits resolution.

The subjects were guided by the software (BioPatRec [6]) to execute and hold the motion during 3s, and relax during 3s between each contraction. Three repetitions of each movement result in 9s of raw MES information. The movements were hand open and close, wrist flexion and extension, and pro/supination, as well as all their possible combinations resulting in 26 motions plus rest.

Seven subjects participated in this study and 4 of them had previous experience with the task, however, the remaining 3 performed the task for the first time. The recording sessions, together with the relevant subject's information, are available in the BioPatRec's bioelectric signals repository under the folder "6mov8ChFUS_MLP_Th" [6].

We have previously found that under the presented recording method, 70% of the contraction time (cTp) normally eliminates periods of absent MES while conserving the isometric part of the contraction. This resulted in 121 time windows of 200 ms per movement (50 ms time increment), see [6] for further explanation on the signal processing and feature extraction.

Four time-domain signal features (mean absolute value, wave length, zero crossings, and slope sign changes) were extracted from each time window in order to from the feature vectors later used to feed the classifier.

### B. Classifier Topology and Training

As opposed to previous work where independent MLPs were used per DoF [11], [12], a simplified single MLP was employed in this study. The MLP had 32 input neurons (4 features x 8 channels), 2 hidden layers of 32 neurons each, 7 output neurons (six motions plus rest), and a sigmoid activation function. The training method was backpropagation with $\eta$ □ 0.1 learning rate and $\alpha$ □ 0.1 momentum. The training was stochastic by randomly supplying 70% of the available training sets per learning iteration. A maximum of 200 iterations was allowed for convergence. The total of feature vectors was divided in 40% training, 20% validation and 40% testing. The feature vectors on the testing set were not presented to the MLP during the training process, and were only used to compute the offline accuracy once the network was trained. One hundred trainings per subject were conducted to compute the average offline performance. Cross-validation was performed by randomizing the feature vectors belonging to the training, validation and testing sets before each network's training.

Additionally, we have previously found in similar experiments that using half of the randomized testing and validation sets produced similar accuracies while reducing training time and improving cross-validation [6]. Therefore 24 and 12 feature vectors per movement were used for training and validation respectively, while 49 were used for testing.

During preliminary research we found that a concurrent issue was the false positives of mixed movements while performing individual ones. For example, supination was easily predicted as intended motion during the execution of hand open or close.

An analysis of the output firing strength suggested that misclassification could be considerable reduced by adjusting the activation threshold of the output neurons. The artificial neuron's firing is governed by its activation function, which traditionally has a limited range, and although the firing strength can vary through the activation range, the prediction of a motion is made binary for simplicity. Especially if proportional control can later be implemented using the average signal strength [14]. A visual indicator was created to individually setup the activation thresholds for each output neuron during real-time classification. A similar visual strategy has been employed by Hargrove *et al.* to setup binary classification threshold to decode individual motions using linear discriminant analysis (LDA) [3]. This approach is reasonably useful in the clinical settings as it allows easy customization of parameters according to individual needs.

False positives have been observed to be more detrimental to controllability than false negatives [3]. Therefore as an additional measure for the reduction of false positives during real-time prediction, the floor noisy during the relaxation period of the recording session was used as a minimum value to overcome before further proceeding with classification. The floor noise value corresponded to the average of the mean absolute value of all channels. If the strength of the signal was lower than the floor noise, the classifier predicted the "rest" class by default.

### C. Real-Time Evaluation

The "motion test" introduced by Kuiken *et al.* [4] was used as the real-time valuation evaluation tool. Its implementation in BioPatRec and further description can be found in [6] . It briefly consists on requesting the subject to execute the different motions in a randomized order while evaluating the following key performance indicators.

- ***Selection time.*** This is the time between the first prediction different than rest, and the first correct prediction. It includes the time window length.
- ***Completion time.*** Using the same trigger as the selection time, the completion time elapses on the 20$^{th}$ correct prediction.

- ***Completion rate.*** This is the percentage of motions that achieved 20 correct predictions before timeout.
- ***Real-time accuracy.*** This is reported as the percentage of correct predictions over the total number of predictions during the completion time.

The motion test was conducted after modifying the output threshold for the movements that were easily misclassified when not intended. The subject was asked to execute each movement individually while the thresholds of misclassified movements were adjusted accordingly. Then, the subject was asked to perform the motions with modified threshold in order to verify that the adjustment will still allow that specific movement to be predicted when intended, see Fig. 1.

The motion tests consisted in 2 trials of 3 repetitions of each movement. The time out for motion completion was 10 s. A prediction was made every 50 ms and the average processing time was 20 ms, therefore the fastest selection time can be 220 ms and the fastest completion time 1.17 s considering 20 correct predictions.

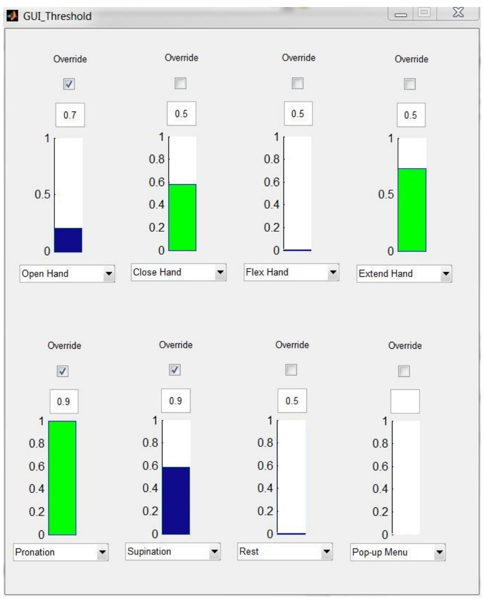


Fig. 1 Graphical user interface used the set up the activation threshold for the output neurons. The height of the bar indicate the prediction strength and the color shows the neuron's state: active (green) or not (blue). The default activation value is 0.5. The subject was performing Close Hand + Extend Hand + Pronation in this example

### *D. Classifier Implementation*

The classification strategy presented in this work was implemented in BioPatRec, an open source framework for the development of advanced prosthetic control strategies based in pattern recognition algorithms [6]. BioPatRec's modular design allows a seamless implementation of algorithms on signal processing; feature selection and extraction; pattern recognition; and, real-time control. It includes all the necessary routines for the myoelectric control of virtual limbs, prosthetic devices, or game control; from data acquisition to real-time evaluations, including a virtual reality environment. Furthermore, it provides a repository of bioelectric signals for algorithm's benchmarking on common data sets.

## 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 (~ ±2.7σ); and diamond markers represent the mean values.

### *A. Offline Performance*

The average offline accuracy was 94.7% (±3%), 92.1% (±4%) and 92.6% (±3%) for 1 (individual), 2, and 3 mixed movements respectively. The average accuracy for all subjects and movements was 92.9 % (±3%). The rest motion was consider together with the individual motions. These results are illustrated in Fig. 2.

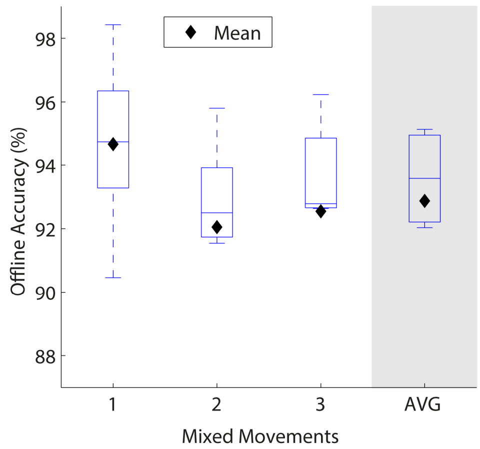


Fig. 2 Offline accuracy grouped by the number of mixed movements

### *B. Real-Time Performance*

The average selection time was 0.50s (±0.2s), 0.79s (±0.3s) and 0.89s (±0.3s) for 1 (individual), 2, and 3 mixed movements respectively. The average selection time for all subjects and movements was 0.76s (±0.3s). These results are illustrated in Fig. 3, where it can be seen the selection time increasing together with the number of mixed movement. This is mainly because the first prediction was normally missing one of the requested motions.

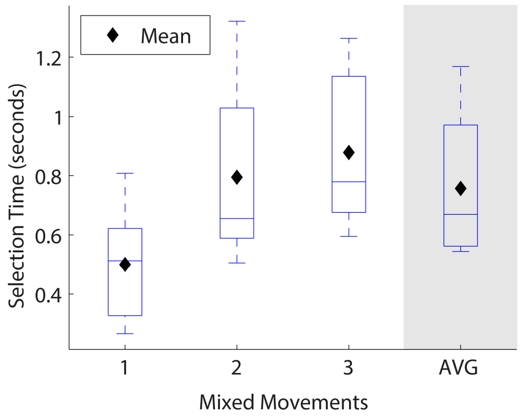


Fig. 3 Selection times grouped by the number of mixed movements

The average completion time was 2.2s (±0.7s), 2.3s (±0.3s) and 2.5s (±0.6s) for 1 (individual), 2, and 3 mixed movements respectively. The average completion time for all subjects and movements was 2.3s (±0.5s). These results are illustrated in Fig. 4.

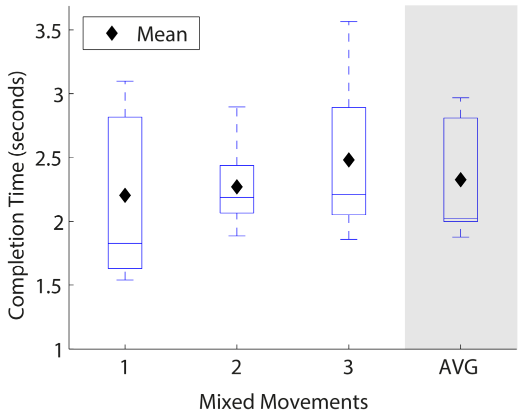


Fig. 4 Completion times grouped by the number of mixed movements

The average completion rate was 0.99 (±0.03), 0.98 (±0.03) and 0.96 (±0.04) for 1 (individual), 2, and 3 mixed movements respectively. The average completion rate for all subjects and movements was 0.97 (±0.02). These results are illustrated in Fig. 5.

The cumulative completion rate is shown in Fig. 6 where it can be seen that 80% of the motions were completed by the more experienced subjects before 2.32 seconds, as oppose to only 52% by the first timers.

The average real-time accuracy was 65.2% (±13.6%), 59.6% (±6.5%), and 54.4% (±9.4%) for 1 (individual), 2, and 3 mixed movements respectively. The overall accuracy was 59.3% (±8.1%). These results are illustrated in Fig. 7.

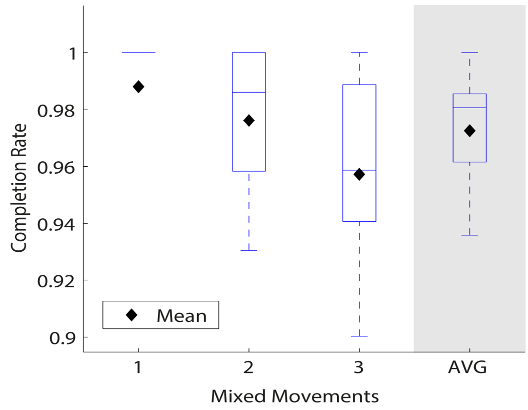


Fig. 5 Completion rate grouped by the number of mixed movements

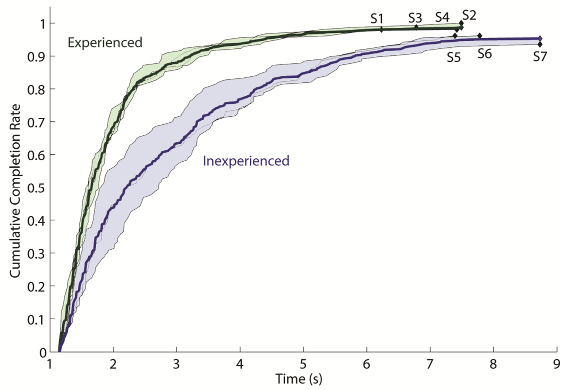


Fig. 6 Illustration of the cumulative completed motions versus time. The subjects with more exposure to the task (S1-S4) show faster and higher completion rates in comparison to first timers (S5-S7)

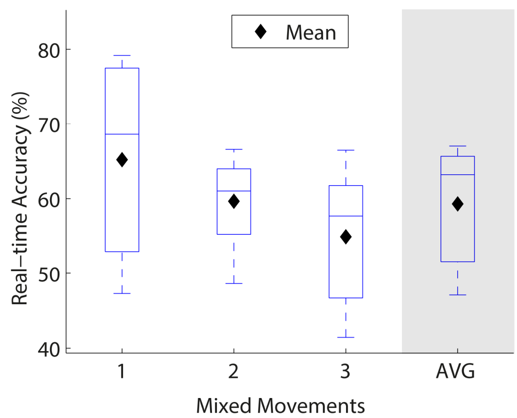


Fig. 7 Real-time accuracy grouped by the number of mixed movements

*C. Applications*

In order to demonstrate the applicability of the presented classification strategy, it was incorporated into BioPatRec to allow the simultaneous control of a multifunctional prosthetic device and a virtual hand (virtual and augmented reality), Fig

8. It was also employed to substitute keyboard strokes for game control, which is aimed to be used a neuromuscular rehabilitation tool. Videos of these demonstration are available online on BioPatRec's project website [15].

Fig. 8 Demonstrations on the classifier used for the simultaneous control of a multi-functional prosthesis (top-left inset); a virtual hand in augmented reality (top-ring inset); and game control (bottom-right inset). The bottom-left inset shows a trans-radial amputee controlling a virtual hand to demonstrate the viability in subjects with missing limbs

## IV. Discussion

A concern worth of attention when planning to substitute individual by simultaneous control, is the loss of stability when aiming to move a single DoF. Our results show the highest real-time accuracy and completion rate, as well as the fastest selection and completion time, for single motions over the mixed ones, thus reassuring the approach of simultaneous classification without compromising individual control. Further research on control algorithms aiming to reduce spurious classifications and improve controllability is currently performed by our group as well as tests on amputee subjects.

In this work, the electrodes were only placed around the forearm as oppose to previous implementations where additional electrodes were also paced in the biceps muscle [10]. The biceps provide independent information on the supination movement, thus potentially facilitating classification. Furthermore, less electrodes were used in comparison with previous work [9]. However, despite the simplifications made in this study, the MLP with variable threshold outputs achieved higher offline accuracies than previously reported. It is worthy of notice however, that no fair performance comparison can be made between related studies due to the several variables involved in the methodology. The differences range from the electrode type and positioning; through acquisition protocols; to subject's anatomy, skills and experience. This stresses the importance of using common data sets and a common platform for the comparison of different algorithms. BioPatRec and the data generated in this study provide an openly available solution for this problem.

The results presented in this work should only be used as an indication of the feasibility of such a system. The absolute values of speed and accuracy are dependent on the processing hardware and the employed real-time test respectively. The same algorithm running in different hardware will have different response time. The subject's attention and motivation during the motion test might also alter the absolute results, as one can be easily distracted or misinterpret requested motions, thus resulting in delays and accuracy decay. Furthermore, additional subject training is known to improve their classification results [16]. We observed such impact in this study as illustrated in Fig. 6 where considerable difference can be observed between subjects with previous experienced in the task, and first timers.

All the discussed variables so far suggest that the results presented in this work are likely to be lower than the actual potential of the classification strategy. For example, more practice, electrodes and their selective placement including additional muscles, are likely to improve these results. However, to truly evaluate the real performance of any prosthetic control strategy, further testing on clinical settings is necessary.

## V. Conclusion

The decoding of mixed movements is a necessary step towards a more natural control of artificial limbs. In this work, we demonstrate the feasibility of simultaneous motion classification for the real-time control of artificial limbs. Furthermore, the proposed MLP implementation using variable threshold outputs can be potentially used in the clinical settings due to its operation simplicity and practicality.

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