Design of Continuous EMG Classification approaches towards the Control of a Robotic Exoskeleton in Reaching Movements

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***Abstract*— Myoelectric control of rehabilitation devices engages active recruitment of muscles for motor task accomplishment, which has been proven to be essential in motor rehabilitation. Unfortunately, most electromyographic (EMG) activity-based controls are limited to one single degree-of-freedom (DoF), not permitting multi-joint functional tasks. On the other hand, discrete EMG-triggered approaches fail to provide continuous feedback about muscle recruitment during movement. For such purposes, myoelectric interfaces for continuous recognition of functional movements are necessary. Here we recorded EMG activity using 5 bipolar electrodes placed on the upper-arm in 8 healthy participants while they performed reaching movements in 8 different directions. A pseudo on-line system was developed to continuously predict movement intention and attempted arm direction. We evaluated two hierarchical classification approaches. Movement intention detection triggered different movement direction classifiers (4 or 8 classes) that were trained and tested over a 5-fold cross validation. We also investigated the effect of 3 different window lengths to extract EMG features on classification. We obtained classification accuracies above 70% for both hierarchical approaches. These results highlight the viability of classifying online 8 upper-arm different directions using surface EMG activity of 5 muscles and represent a first step towards an online EMG-based control for rehabilitation devices.**

I. Introduction

Rehabilitation devices such as robotic exoskeletons have shown great potential in the field of motor rehabilitation as they permit a repeatable and intensive proprioceptive stimulation of paralyzed limbs in terms of goal-oriented mobilizations. However, robot-aided treatments do not necessarily contribute to regain motor function unless active and voluntary participation of patients' paretic muscles is present during movement [1], [2]. In this context, myoelectric interfaces for controlling robotic exoskeletons constitute a promising potential tool to effectively involve muscle recruitment for motor task accomplishment.

Current myoelectrical interfaces applied in rehabilitation chiefly focus on the control of single-DoF actuators based on EMG amplitude. EMG-based control systems that continuously modulate mechanical assistance provided by a robotic exoskeleton have been developed for single-DoF movements such as wrist extension [2] and hand grasping [3]. Nevertheless, while continuous control of a single DoF based on EMG activity can be feasible, the decoding of myoelectric signals during movements that involve several DoFs simultaneously remains still challenging, especially in stroke patients. Simpler approaches based on EMG-triggered interfaces have also been applied in order to train multi-joint tasks such as multi-directional movements with the upper arm [4]. This approach enables to trigger the movement of the actuator without the need of self-producing any actual movement, which may allow even highly-impaired participants to activate robot assistance [5]. Nonetheless, although EMG-triggered approaches might reinforce muscle strength by requiring constant activation of specific muscles above a certain threshold during movement, they fail to provide specific feedback regarding the user's inappropriately co-activated EMG patterns. On the other hand, discrete approaches in which rehabilitation devices are triggered by EMG activation only at the trial onset fail to provide feedback about the muscle recruitment continuously during the entire movement execution.

In spite of inappropriate co-activation of muscles due to incorrect muscle synergy recruitment in stroke patients [3]–[6], successful results in classifying residual EMG activity of stroke patients have been reported [7],[8]. Diverse functional movements involving multiple joints at the upper-limb, wrist and hand levels have been discriminated based on the residual activity of stroke patients, achieving better results in moderately impaired patients (71.3%) than in severely paralyzed subjects (37.9%) [7]. From these results, it is concluded that the recognition of different discrete movements involving several upper-limb DoFs based on residual EMG can still be feasible.

Therefore, myoelectric interfaces for the EMG continuous classification of discrete multiple-joint movements present a promising option for the training of functional movements using rehabilitation devices. In this work, we developed a "pseudo-online" system to predict movement intention and attempted direction during point-to-point reaching movements in the horizontal plane based on the EMG activity of five upper-limb muscles in healthy participants.

II. Methods

A. Experimental Protocol

Eight right-handed naïve healthy participants (5 males, age 25±2.74) were involved in the experiment after giving written informed consent to the procedures approved by the

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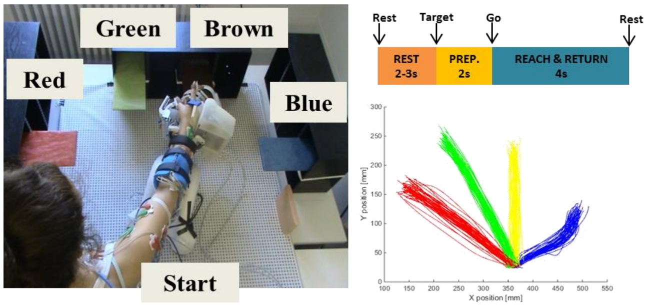

Fig.1. Left: a participant performing a reaching task towards four different directions towards red, green, brown and blue and return to the rest position from red, green, brown and blue. Right: trial timing and reaching trajectories of one participant towards the targets.

ethics committee of the Faculty of Medicine of the University of Tübingen, Germany. Participants performed reaching movements with their right arm while sitting and wearing the IS-MORE 7-degree of freedom upper-limb exoskeleton (Tecnalia, San Sebastian, Spain). The motor task consisted of reaching movements in the horizontal plane from a predefined start position towards four different goals indicated by targets of different colors around the workspace (see Fig.1) and returning to the start position. Participants moved their upper-limb actively and had to overcome minimal friction and weight of the exoskeleton attached to their limb in order to perform the movements.

Each participant performed 50 reaching trials from the start position towards each direction (four reaching directions) and return to the start position (four returning directions), completing 200 trials in total in 5 separate runs. An inter-trial rest period of a random time between 2 and 3 seconds was given to avoid fatigue. After the inter-trial rest period, an auditory cue indicated the participant the color of the target to reach in that trial and two seconds later a "Go" cue indicated the instruction to start the movement. The participants had 4 seconds to perform the reaching movement towards the indicated target and return to the resting position (trial timing schema in Fig.1). We placed five bipolar Ag/AgCl electrodes from Myotronics-Noromed (Tukwila, WA, USA) over the: 1) long head of biceps, 2) external head of triceps, 3) anterior portion of deltoid, 4) lateral portion of deltoid and 5) posterior portion of deltoid. The ground monopolar electrode was placed over the right clavicle. The EMG signals were acquired at 2500Hz using a bipolar amplifier (Brainproducts, Gilching, Germany). Participants moved the exoskeleton on top of a mat with printed DATAMATRIX codes, which were tracked by a webcam located in the base of the exoskeleton. The position of the forearm in the horizontal plane was acquired at 18Hz.

B. *Data Processing*

The EMG signals were notch filtered, band-pass filtered between 10Hz and 500Hz using a 4th order Butterworth filter and rectified. For all filtering processes, we employed a causal filter that can be used for online real-time applications. Kinematic data were processed for artifact removal and low-pass filtered at 1.5 Hz using a 4th order Butterworth filter. We synchronized EMG and kinematic data off-line and upsampled the kinematic data to the EMG data frequency by applying cubic interpolation. Forearm movement velocities in the horizontal plane were computed offline from acquired position data. We searched for four time points along each trial:

- EMG activation onset and end: we applied the Teager–Kaiser energy operator (TKEO), rectified and low-pass filtered at 50Hz (2nd order Butterworth) the previously band-pass filtered EMG signals. Mean (μ) and standard deviation (σ) of the rest period prior to each trial (baseline) were computed. We used a threshold-based method to detect the onset on the EMG activation where threshold T was determined for each muscle as follows:

  $$T = \mu + h\sigma$$

  where h is a preset variable, defining level of the threshold. Threshold level was set to 20 since it was empirically found to be the most robust and introduced the smallest detection errors. Onset and end time for each muscle were identified as the first and last point when the smoothed signal exceeded the threshold T for more than 30ms, respectively (needed to be considered a muscle contraction and not an artefact) [9]. Each movement direction was initiated by a different muscle depending on the initial starting point in each trial and the trajectory of each user to approach the targets. We therefore considered as overall EMG activation onset and cessation of each trial the earliest onset and latest end from the five muscles in order to generalize for all trial types and participants.

- Movement onset: after convolving and normalizing the absolute value of the base of the exoskeleton in the horizontal plane, we considered as movement onset the time point in which the base reached the 5% of the maximum velocity amplitude registered during that trial [10] after the "Go" cue (see Fig. 2). The average time between EMG activation onset and actual movement onset detected by the exoskeleton was 0.55±0.07 seconds.

- Transition time used to split the data between reaching and returning phases: was considered as the time where the participant reached the furthest point with reference to the starting position in the horizontal plane in each trial, before starting the returning phase (see Fig. 2).

The period starting from the EMG activity onset until the cessation of EMG activation, was considered as a movement-related period and labeled with the performed reaching direction. Participants used an average time of 2.06±0.18 and 1.34±0.24 seconds to complete reaching and return movements, respectively.

C. *EMG Feature Extraction and Classification*

In order to test how our classifier would perform online, we constructed a pseudo-online feature extraction and classification process. We computed the waveform length of the previously recorded EMG signals on sliding windows with a step size of 50ms, i.e. every 50ms of data. We used three different window lengths for feature extraction (1s, 500ms and 200ms) to test the effect of using larger or smaller amounts of preceding EMG data for movement prediction. The input for training and testing the classifiers therefore consisted in a vector of five waveform length values (one from each muscle) extracted from the EMG data comprised in each sliding window all along the training or testing dataset, respectively. For the testing dataset, the classifiers generated a prediction for every input value (i.e. every feature vector extracted from each sliding window), thus giving an output every 50ms (20Hz). Hence, the output given at a specific time point corresponded to the classification of the features extracted from the EMG data window preceding that point. Training and testing data were recorded within the same sessions and normalized using the Z-scores computed from the training data set. We trained and tested different support vector machines (SVM) with radial basis function kernel using LIBSVM [11]:

a) Movement attempt classifier (MovC): binary classifier trained using resting activity data from inter-trial periods and movement-related data (including the EMG during the forward reaching and backward returning movements in the eight different directions).

b) Direction classifiers: we built three different classifiers or detecting the direction attempted by the participant:

b.1) Reaching classifier (ReachC): a 4-class classifier trained with data of the four forward reaching directions that included Blue-Forward (Bl-F), Red-Forward (Red-F), Green-Forward (Gr-F) and Brown-Forward (Br-F).

b.2) Return classifier (ReturnC): a 4-class classifier trained with data of the four backwards returning directions that included (Blue-Backwards (Bl-B), Red-Backwards (Red-B), Green-Backwards (Gr-B) and Brown-Backwards (Br-B).

b.3) General classifier (GeneralC): an 8-class classifier trained with data of the four forward reaching and four backwards returning directions.

D. Performance Evaluation

All classifiers were trained and tested independently within a 5-fold cross validation (CV). In each fold, each classifier was trained with concatenated EMG data of four entire runs (80% of data) and tested over the remaining fifth run (20% of data). We evaluated each classifier exclusively during the same movement periods that were used to train them. Therefore, MovC classifier was evaluated during the whole testing run (including rest, forward reaching and backward returning periods), while ReachC and ReturnC were evaluated only during forward reaching and backward returning periods, respectively. Testing data for GeneralC included both forward reaching and backward returning periods.

a) Influence of window length in feature extraction for classification

In this work we first evaluated the effect of the window length used for feature extraction in the classification of movement intention (using MovC) and forward direction (using ReachC) in the time period short after the EMG activation onset and during the reaching movement. All trials (50 trials x 8 participants) were aligned with reference to the EMG activation onset. For each window length, we evaluated the amount of points that were correctly detected as movement state (using MovC) and classified as the correct reaching direction (ReachC) in each time point after the EMG onset. The time interval between EMG onset and the time when the MovC classifier reached classification accuracy above 98% was considered as movement detection latency.

Due to small sample size we performed Friedman nonparametric tests for investigating the effect of the window length factor on the 1) movement detection latency for MovC, 2) classification accuracy for MovC and 3) classification accuracy for ReachC. Post-hoc pairwise comparisons of the three window lengths were performed and controlled for multiple comparisons using Bonferroni correction (statistical significance considered when $p < 0.016$).

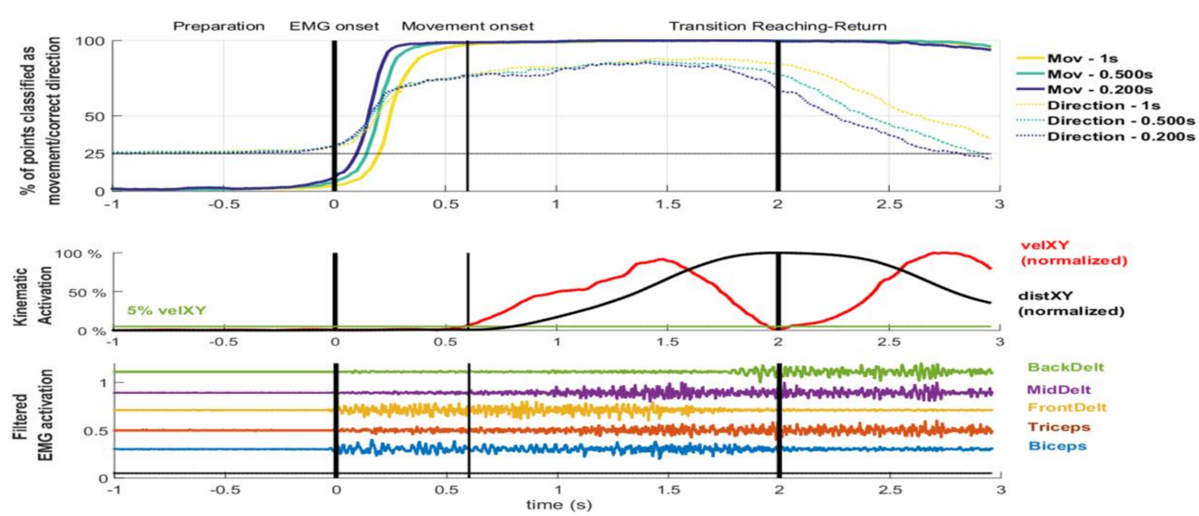

Fig. 2. Average classification accuracy of all trials for all 8 participants of the movement intention binary classifier and the ReachC four-class direction classifiers. In x axis, 0 corresponds to the EMG activation onset. The continuous lines represent the correct classification rate of the movement attempt binary classifier using different window lengths for feature extraction. The dashed lines correspond to the correct classification rate of the multiclass direction classifier. The line at 25% represents the chance level of ReachC classifier. Below, normalized kinematics activity and filtered EMG activations of a representative trial. The black line represents the distance of the base of the exoskeleton from the initial starting point while the red line represents the velocity. Upper-arm muscle activities are plotted at different heights. EMG and movement onset and transition point are represented with vertical lines.

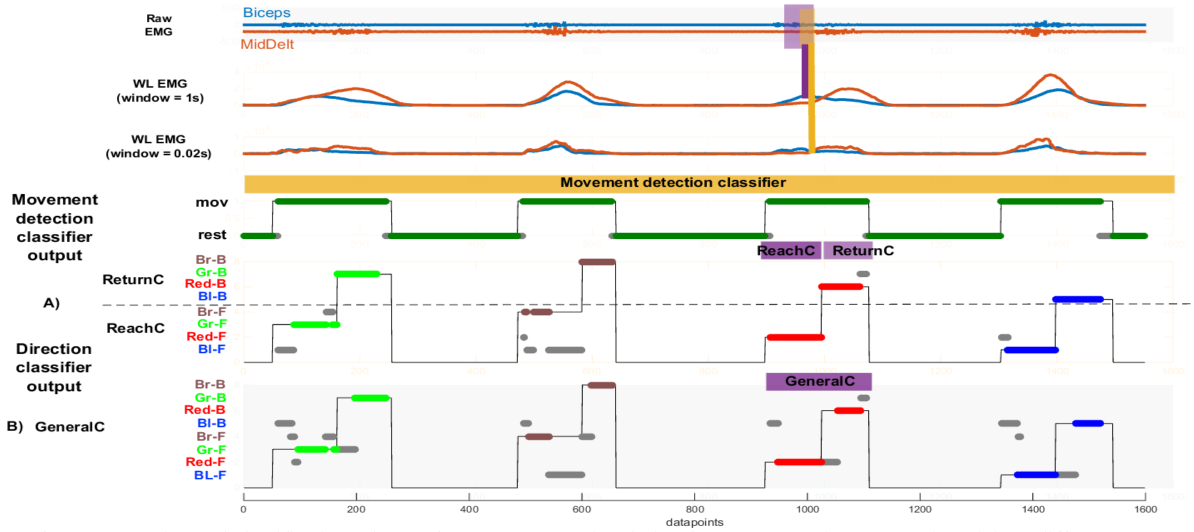

Fig. 3. EMG feature extraction and classification schemes for Strategy A and B during four representative consecutive trials to different targets. MovC is active during the whole testing run and gives an output indicating if movement intention has been detected (mov) or not (rest). Below, the continuous outputs of each direction classifiers. Correctly classified points are plotted in green color (MovC classifier) or in the color of the target indicating the movement direction (ReachC, ReturnC and GeneralC), while misclassified points are gray.

b) Multiple direction continuous hierarchical classification approaches

Subsequently, we evaluated two different approaches for multiple direction continuous classification. In strategy A), two independent 4-class classifiers were used to detect the movement direction intended by the user: ReachC during the forward movement (Bl-F, Red-F, Gr-F, Br-F) and ReturnC during the backward phase (Bl-B, Red-B, Gr-B, Br-B). In strategy B), one single general 8-class classifier was used during the whole movement to predict the movement direction. The continuous off-line classification schemas for both strategies are shown in Fig. 3.

The MovC was trained with the waveform length extracted from 200ms-long windows, whereas we used 1s-long windows for all direction classifiers, as they were opted as the windows sizes that best worked for each classifier type (see Results). Each classifier received as input the waveform length continuously extracted from the filtered five EMG signals (using the respective window size) during the whole testing run and gave an output every 50ms (20Hz). We estimated the overall performance of each classification strategy considering the output of the multiple direction classifier (ReachC, ReturnC, GeneralC) only if movement was detected by MovC, i.e. we used a hierarchical approach**.**

III. Results

A. Influence of window size in feature extraction for classification

Classification accuracies before and after EMG onset for MovC (continuous lines) and ReachC (dashed lines) are shown in Fig. 2, upper plot. Movement detection during preparation (arm in rest position) was nearly zero, while movement direction correct around chance level (25%). The time with reference to the EMG onset to reach a correct classification rate for movement detection above 50% (chance level) and above 98% by the binary classifier MovC using different window sizes for feature extraction are reported in Table I. Faster EMG activation detection was achieved with shorter window sizes of 200ms and 500ms, significantly better than with 1s-long windows (p=0.012 and p=0.011), and achieving a mean classification accuracy of 93.03% and 93.55%, respectively.

The effect of using 200ms and 500ms of precedent data for feature extraction was almost significant in movement detection latency ($p = 0.017$) but not significant in classification accuracy ($p = 0.069$). As it can be observed in the upper plot in Fig. 2, the classifier trained using a window size of 200ms (dark blue line) presents a more rapid increase in the detection accuracy of movement short after EMG onset. Because of this, a 200ms-long window was selected for the feature extraction of EMG signals for MovC used in the following hierarchical approach.

For the pattern recognition of the forward reaching direction by ReachC, using longer EMG windows (1s) resulted in a higher overall discrimination accuracy of 78.28% (see Fig. 2). However, the influence of the window length was not found to be significant for reaching movement recognition ($p < 0.016$) in average for the entire

Table I MovC and ReachC classification accuracies and delays from EMG onset.

Classifier type	**Measured Metric**	**Window size for feature extraction**		
		1s	***500ms***	***200ms***
MovC	Time from EMG onset to acc. > 50% (s)	0.28	0.22	0.18
	Time from EMG onset to acc. > 99% (s)	1.06	0.96	0.84
	True Positive Rate (%)	92.47	92.84	93.03
ReachC	True Positive Rate* (%)	78.28	76.15	73.77

* Evaluating points where the MovC classifier detected movement intention correctly only.

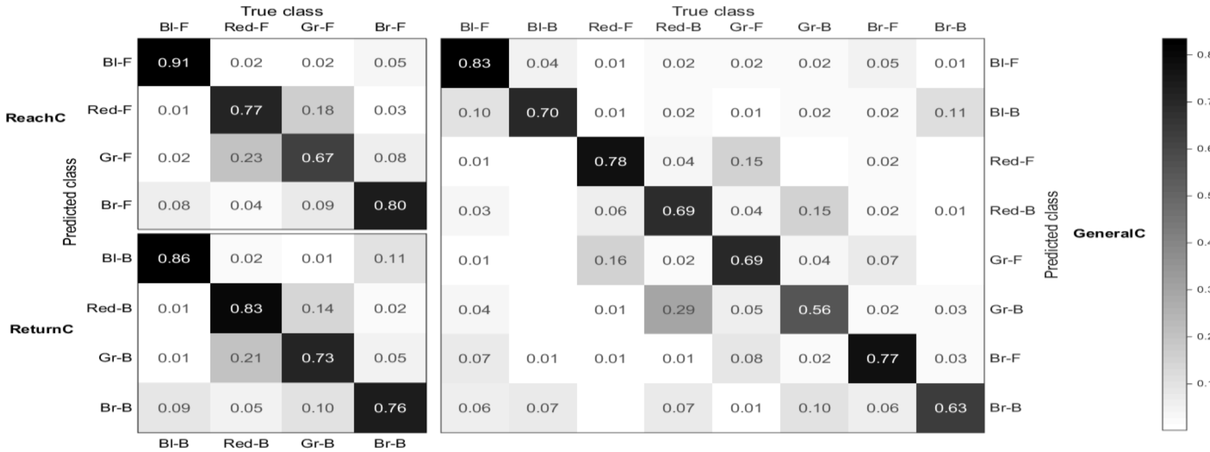

Fig. 4. Confusion matrices of 4-class ReachC, 4-class ReturnC and 8-class GeneralC classifiers show the correct (in diagonal) and incorrect (out of the diagonal) classification rates of each movement direction. To calculate the off-line classification rates, only points where movement intention was detected by the binary classifier within the reaching and returning phases were considered for evaluation.

reaching phase. As it can be observed in Fig. 2, however, unlike classifiers trained with longer window lengths (dashed yellow line), shorter windows (dashed dark blue line) present a drop in classification accuracy as the reaching end goal (transition) is approached. We therefore opted for a 1s-long window for the waveform length extraction used as input for the direction classifiers used in both hierarchical classification approaches. Classification performance dropped progressively to chance level during the returning phase, due to ReachC classifier uncertainty when recognizing such unfamiliar EMG patterns.

B. *Multiple direction continuous hierarchical classification approaches*

Fig. 3 describes the feature extraction and classification schemes for Strategy A and B during four representative consecutive trials to different targets. The average percentage of points correctly classified as movement or rest state (colored in dark green in “Movement detection classifier output”) during the whole testing run by MovC over the 5-fold CV was 93.03%. Points plotted in colors of the different targets were points correctly classified, while gray points represent misclassified points. We obtained an overall performance accuracy of 78.28% and 79.52% for ReachC and ReturnC 4-class classifiers, respectively (78.9% for strategy A). On the other hand, in strategy B, a single 8-class general classifier was accurate on average in 70.62% of the points considered for evaluation (see Fig. 4).

IV. Discussion

This study represented the first step towards an online electromyographic interface to continuously control reaching movements of a robotic upper-limb exoskeleton.

We explored the effect of window length to calculate the features in the direction classification accuracy and onset detection. Our results indicated that a relatively short (200ms-500ms) window size resulted in faster EMG activation detection short after EMG onset, without compromising the classification accuracy [14],[15]. Nevertheless, the influence using precedent EMG data of a window between 200ms and 1s did not show to be significant for movement direction recognition. However, classifiers trained and tested using features extracted from shorter windows of data decreased in performance as the transition point was approached. This drop was the result of an increasing presence of data points that were closer or already belonged to the returning phase (in case of trials with shorter reaching phase).

The time between the EMG and actual movement onset was higher than the delays reported in the literature for upper-arm free movements without constraints [14]. We hypothesized that the weight and mechanical friction imposed by the exoskeleton required longer EMG activations for movement initiation.

During multiple directions classification, the reaching movement towards adjacent targets was commonly misclassified as one of the neighbor targets. A similar result was observed when classifying returning directions from contiguous targets (see confusion matrices in Fig. 4). As it can be observed in Fig.1, the trajectories towards the green targets did not differ too much from the trajectories towards the adjacent targets, complicating the discrimination between these similar movement directions. From these results we concluded that a workspace maximizing inter-target distance may reduce misclassification errors.

We proposed a hierarchical myoelectric interface control, in which a first movement intention binary classifier triggered a second four-class/eight-class classifier that identifies the reaching direction attempted by the user. A hierarchical approach avoided incrementing the number of possible outputs in the multiclass classifiers, leading to higher performance than in previous works where a single classifier was used [15]. Using the selected window sizes each classifier (200ms for movement detection, 1s for attempted direction), we were able to recognize participants’ motion intention above chance level (50%) in all cases before actual movement onset. At this point, the intended direction of the user was recognized with 51.21% accuracy (lowest accuracy during the trial after movement detection; change level being 25%), revealing certain classifier uncertainty during the movement initiation interval. However, classification rates increased rapidly during the initial phase after EMG activation movement. As the MovC reached acceptable movement detection (above 98%) within 440ms after EMG onset, the intended direction was discriminated already with 73.77% accuracy. This indicated that acceptable direction recognition could be achieved before actual motor action, which is an important point to study in cases of paralyzed limbs.

Using two separate classifiers during each task phase (reaching and returning) might constitute a good option in those patients whose residual EMG activity is clearly different between the forward and backward movements. Hence, a more accurate feedback using classifiers with less output possibilities (and therefore more accurate) could be provided. However, a classifier that considers only a limited possible discrete directions in each phase of the movement (only forward directions are considered during the reaching phase and backwards during returning phase) will fail to provide the correct feedback to the users in cases where the direction of the intended movement is opposite to the expected one (e.g. when the EMG activation patterns indicate an intention to move the arm backwards to the resting position rather than moving forward during a reaching phase). Nevertheless, with the general classifier we obtained an average classification accuracy of 70.62% (significantly above chance-level=12.50%) confirming that controlling the exoskeleton movement online in all 8 directions could be feasible using 5 bipolar surface EMG electrodes only. Most misclassification events arose nearby the transition points between the reaching and returning phases. A protocol with slower transitions for direction change (e.g. by introducing a short inter-phase rest) would facilitate the differentiation of the phases, thus reducing misclassification errors. Also, features extracted using shorter windows (containing information from only recent precedent EMG activity) were more sensitive to fast changes in EMG patterns (e.g. involuntary reflexes, changes of movement direction) than longer windows. Because of this, using shorter window sizes would certainly improve the classification accuracy of a general multi-directional classifier, enabling a faster detection of changed EMG activations in the transition between two different movement directions.

V. Conclusion

In this work we developed a "pseudo-online" classification system to predict movement intention and attempted direction during point-to-point reaching movements in the horizontal plane based on the EMG activity of five upper-arm muscles in healthy participants. Continuous prediction of movement intention in real time during functional movements is essential in order to provide users a contingent feedback about their muscle recruitment using myoelectrically controlled robotics. Acceptable classification accuracies above 70% were achieved in this off-line evaluation with healthy participants performing reaching movements. Nevertheless, further experiments with healthy participants and stroke patients using this myoelectric interface online are needed to confirm the feasibility of this approach for controlling a robotic exoskeleton in real time.

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