Surface Versus Untargeted Intramuscular EMG Based Classification of Simultaneous and Dynamically Changing Movements

Ernest Nlandu Kamavuako, *Member, IEEE*, Jakob Celander Rosenvang, Ronnie Horup, Winnie Jensen, *Member, IEEE*, Dario Farina, *Senior Member, IEEE*, and Kevin B. Englehart, *Senior Member, IEEE*

Abstract—The pattern recognition-based myoelectric control scheme is in the process of being implemented in clinical settings, but it has been mainly tested on sequential and steady state data. This paper investigates the ability of pattern recognition to resolve movements that are simultaneous and dynamically changing and compares the use of surface and untargeted intramuscular EMG signals for this purpose. Ten able-bodied subjects participated in the study. Both EMG types were recorded concurrently from the right forearm. The subjects were instructed to track dynamic contraction profiles using single and combined degrees of freedom in three trials. During trials one and two, the amplitude and the frequency of the profile were kept constant (nonmodulated data), and during trial three, the two parameters were modulated (modulated data). The results showed that the performance was up to 93% for nonmodulated tasks, but highly depended on the nature of the data used. Surface and untargeted intramuscular EMG had equal performance for data of similar nature (nonmodulated), but the performance of intramuscular EMG decreased, compared to surface, when tested on modulated data. However, the results of intramuscular recordings obtained in this study are promising for future use of implantable electrodes, because, besides the value added in terms of potential chronic implantation, the performance is theoretically the same as for surface EMG provided that enough information is captured in the recordings. Nevertheless, care should be taken when training the system since data obtained from selective recordings probably need more training data to generalize to new signals.

Index Terms—Classifiers, dynamic movement, intramuscular electromyography (EMG), pattern recognition, simultaneous movement.

I. INTRODUCTION

SURFACE electromyography (EMG) is the golden standard technique for controlling currently available upper limb electric prostheses. Several methods have been proposed in the literature in order to improve the control systems [1]–[7]. The methods can be generalized and grouped into conventional methods and pattern recognition-based methods [8].

In conventional methods, features of the EMG signal, such as mean absolute value (MAV), are used as a direct control source in order to drive a device. The first generation of these systems offered an ON/OFF control approach, where one channel of the EMG signal is mapped to one prosthetic function or one control state [9]. If the amplitude exceeds a predefined threshold value, the corresponding function is activated at a constant speed. Multiple functions can be assigned to different channels when multiple signal sites are available. The second generation of conventional control included proportional control, in which the velocity of a selected prosthesis function is proportional to the level of the myoelectric activity [10]. Proportional control allows for more intuitive use, as the control sites can be selected so that each function corresponds to the physiologically appropriate muscle. However, this scheme needs at least two signal sites to implement one physiological degree of freedom (DoF). For example, one signal can be used to derive the velocity of hand opening, while a second signal is needed for hand closing. Therefore, current commercially available prosthetic devices only provide very few controllable DoFs. Pattern recognition is one way to increase the amount of information extracted from muscle signals and to eliminate the need for isolated EMG signals. These algorithms look for patterns of muscle activity across one or more muscle sites rather than relying on independent EMG signals [11].

In pattern recognition-based techniques, it is assumed that there exists a set of distinguishable and repeatable signal patterns in the EMG signal during different types of movements. These systems consist of a feature extraction module and a classifier module. Within classifiers, the two major categories are statistical classifiers and learning classifiers. The statistical classifiers establish the mapping rule by estimating statistical characteristics of the features. The learning classifiers determine a mapping rule using an iterative learning and some cost functions. Several feature extraction techniques have been proposed, including the MAV and the variance of the surface EMG [12]–[14], autoregressive coefficients [15]; the short

time Fourier transform [16] and the wavelet transform [17], [18]. Although different choices of classifiers have also been explored, most classifiers, when tested on steady-state data, provided similar classification accuracy given proper data preprocessing and choice of feature sets [19].

Despite increased performance achieved by controllers based on pattern recognition, they are currently not used in the clinic [20]. Therefore, researchers recently have been investigating the clinical usability of pattern recognition with studies related to the influence of proportional contraction, limb position [21], and electrode shift [22] on pattern recognition, just to mention some of the challenges that face this type of system [11]. The current study focuses on the way in which pattern recognition resolves dynamic and simultaneous data, as a necessary step to assess its potential use and added value compared to the current clinical use of proportional control schemes. One of the problems associated to this myocontrol approach is indeed the fact that current classification techniques for EMG pattern recognition are mostly tested on sustained, steady-state contractions. This imposes sequential control, while the natural control of artificial limbs requires the simultaneous control of multiple DoFs during dynamically changing movements [20], [23]. Pattern recognition control has been attempted on transient scenarios alone [8] and in combined transient/steady state scenarios [24] with successful results. However, the dynamic characteristic of transient data resembles a ramp that lasts for only a few seconds while the remaining part is sustained during sequential movements. In this study, we investigate pattern recognition methods for movements that are entirely changing in intensity and switching over time, including simultaneously performed DoFs.

Another factor that has been pointed out as a drawback of myoelectric control is the lack of independent command sites due to the use of surface EMG that has limited selectivity. It has been suggested that both an increase in the number of DoFs and simultaneous control can be achieved by increasing the availability of independent command sources with suitable interfaces to the nerves or muscles [25].

Intramuscular EMG is recorded from inside a muscle as an alternative signal source for controlling prostheses that may help overcome some of the drawbacks associated with surface EMG [26]. The greater selectivity of intramuscular, with respect to surface EMG, may, on the other hand, be a disadvantage, since the signal may provide local, rather than global information. Nevertheless, it has been shown that surface EMG and intramuscular EMG have equal classification performance [19], [27]. Furthermore, there was no significant difference between surface, targeted and untargeted intramuscular EMG based classification of movements [27]. However, these previous comparisons were made on steady-state and sequential movements only. Thus, it is not known whether surface and intramuscular EMG will perform similarly during simultaneous and dynamically changing movements.

The aim of this study was to investigate the ability of pattern recognition techniques to provide a control scheme that includes simultaneous, dynamically changing movements and to compare the performance of surface and untargeted intramuscular EMG for this purpose.
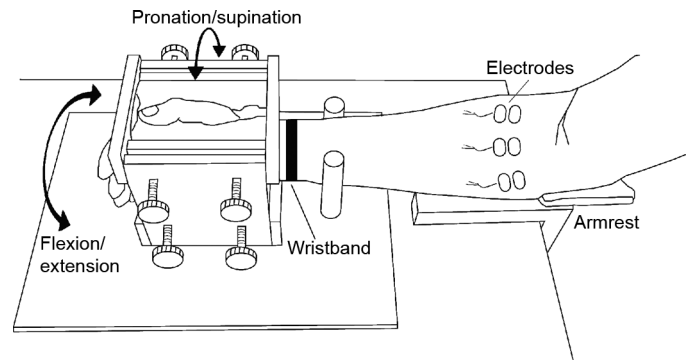

Fig. 1. Experimental setup showing the fixation of the arm.

II. METHODS

A. Subjects

The experiments were conducted on ten able-bodied subjects (six men/four women, age range: 23–26 years). The procedures were in accordance with the Declaration of Helsinki and approved by the Danish local ethical committee (approval: N-20080045). Subjects provided their written informed consent prior to the experimental procedures. The subjects had no history of upper extremity or other musculoskeletal disorders.

B. Experimental Procedures

EMG signals and torque signals were collected during simultaneous, isometric, but dynamically changing tasks of the wrist. The experiment was carried out in three trials with a 5-min rest in between. Each trial included eight combinations of tasks separated by 2 min of rest to minimize the effect of fatigue. The performed tasks were categorized into individual and combined (simultaneous) DoFs in order to test the ability to classify movements in two DoFs simultaneously. The selected DoFs were wrist flexion/extension (first DoF) and wrist supination/pronation (second DoF). The eight tasks were paired: wrist flexion/wrist extension, supination/pronation, simultaneous flexion + pronation extension + supination and simultaneous extension + pronation/flexion + supination. All tasks were dynamically changing from one movement to the other within each DoF and pair of DoFs based on a sinusoidal profile lasting 30 s at moderate torque level. For example, the subject performed flexion followed by extension or simultaneous flexion with pronation followed by simultaneous extension with supination. The first and last three seconds of each profile consisted of rest to obtain data for a *no motion* class, so that the classification problem consisted of nine classes. We used sinusoidal profiles to include dynamic contractions, requiring constant changes in the force (and EMG intensity) level of the performed task. The subjects were seated in a chair with their right arm placed in an armrest (Fig. 1). Subjects were asked to track one profile or two simultaneous profiles depending on whether it was a single DoF or two simultaneous DoFs, as shown in Fig. 2(a) and (b). The order of the eight tasks was randomized; subjects received visual feedback as to how closely they tracked the profiles. The subjects had sufficient time to train and become familiar with the profiles. During trials 1 and 2, the amplitude and frequency (nonmodulated data
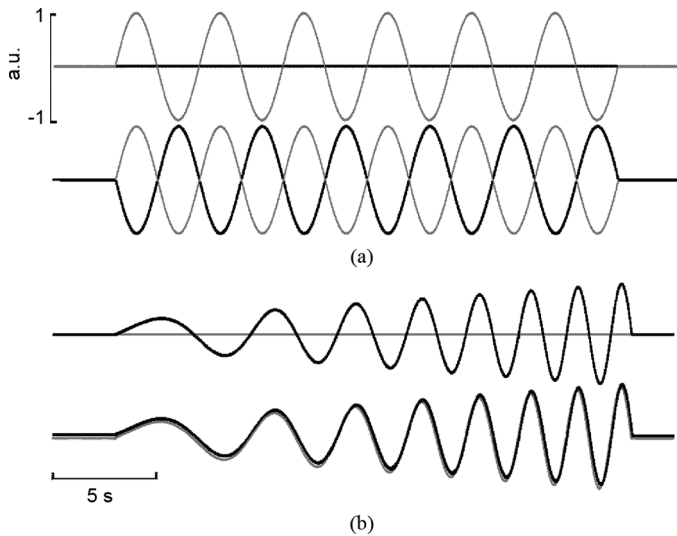
Fig. 2. Movement profiles followed by the subjects. (a) Profiles used in trials 1 and 2 for single DoF (upper plot) and simultaneous DoF (lower plot). (b) Modulated profiles used in trial 3 for single and simultaneous DoF (Frequency range 0.1 –0.5 Hz) the bottom plot in (b) also contains a second sinus in gray. Dark line corresponds to one DoF and gray line to the second DoF.

at 0.5 Hz) of the sinusoidal profile were kept constant, while in trial three these two parameters were modulated (modulated data with frequency range 0.1 –0.5 Hz) as shown in Fig. 2(b).

C. Data Collection

A custom-made hand support incorporating a commercially available dynamometer (Gamma FT-130–10, ATI Industries) was used to provide feedback to the subjects about the level of activation (torque) for each task. Two torque signals were recorded, corresponding to the two DoFs. Six pairs of surface EMG electrodes (Ambu Neuroline 720) were placed equidistantly around the forearm, starting a few centimeters lateral to the ulnar exposure at the point of largest circumference.

The intramuscular EMG was recorded using six bipolar wire electrodes, inserted to reside underneath each surface EMG electrode pair, providing an equidistant distribution around the forearm. Intramuscular wire electrodes were made of Teflon-coated stainless steel (A-M Systems, Carlsborg WA, diameter $50~\mu m$) and were inserted into each muscle with a sterile 25-gauge hypodermic needle. The insulated wires were cut to expose only the cross section at the tip, providing high selectivity. The needle was inserted to a depth of a few millimeters below the muscle fascia and then removed to leave the wire electrodes inside the muscle. All signals were anti-alias filtered and amplified (AnEMG12, OTbioelletronica, Torino, Italy), A/D converted on 16 bits (NI-DAQ USB-6259), and sampled at 10 kHz. A reference electrode was placed around the wrist.

D. Signal Processing

Intramuscular and surface EMG signals were digitally band-pass filtered (fourth order Butterworth filter) between 100–3000 Hz and 20–500 Hz, respectively. Each recording was segmented at the points of zero crossings of the torque signals, between the two movements of a particular movement pair in order to obtain data segments for each class. In case of simultaneous movements, we used the best tradeoff between the crossings of the two simultaneous torque signals. Eight Time domain (TD) [8], [28], seven frequency domain (FD) [19] and 11 time-frequency domain (TFD) [17] features were extracted using a window of 150 ms and a step size of 50 ms for each channel. All features were combined resulting in a 156 dimensional feature space per EMG type.

Two dimensionality reduction methods were investigated and compared with "*no reduction*", namely principal component analysis (PCA) and an unreported method within myoelectric control known as separability and correlation (SEPCOR). Dimensionality reduction was assessed in order to test if the performance can be influenced by the number of features. PCA projects the feature space into uncorrelated variables orthogonal to the direction of maximal variance, such that the first variable describes the largest amount of variance. The number of stored variables depends on the desired minimum cumulative retained variance of the original feature space. SEPCOR is a feature selection technique that stores the features with highest discriminative power and discards features that are highly correlated to the stored features. Thus, features are selected based on maximal allowed correlation [29]. To assess the effect of the aforementioned parameters, PCA was used with minimum variance of 95% and 99% (PCA95 and PCA99); and SEPCOR with maximum correlation of 0.90 and 0.95 (SEP90 and SEP95).

The classification was performed using five commonly used classifiers and the percentage of correct classifications (PCC) was used as performance measure. The *artificial neural network (ANN)* is an emulation of the biological system and consisted of one hidden layer with ten neurons with the hyperbolic tangent sigmoid functions as transfer functions in both the hidden and output layers. The training data were randomly divided so that 70% was used in the training and 30% for validation in order to minimize overfitting. Each network was trained 50 times and the network with the highest PCC on the validation data was used on the test data. *K-nearest neighbor (kNN)* uses a distance measure (Euclidian in our case) to classify new observations based on the k nearest observations in the training set. The value of k was set to five. *Linear discriminant analysis (LDA)* is a statistical classifier that aims at finding combinations of features that optimally discriminate between classes. A *support vector machine (SVM)* offers a more complex approach for separating between two classes. A linear kernel was used, where the optimal boundary was found by maximizing its distance to the nearest training observations on both sides. The first mode of SVM used the one against all (OAA) approach, which separated each class with respect to all the others together, where the final decision was obtained by selecting the class maximizing the discriminant function. The second mode of SVM classifier used the one against one (OAO) approach, which provided a decision for each pair of classes, where the final decision was obtained through a majority vote.

E. Data Analysis

The analysis for the nine classes (flexion, extension, pronation, supination, simultaneous flexion + supination,

simultaneous extension + pronation, simultaneous flexion + pronation, simultaneous extension + supination and no motion) problem was carried out in two steps. First, we used a four-fold cross validation procedure using data from trial one and trial two (nonmodulated). Each fold was comprised by assigning a half trial as testing data and the remaining one and half trial as training data. This is referred to as the four-fold validation test. Second, we used a similar approach where we included the modulated data (trial three). For this part, we performed two four-fold validations: 1) between trial one and trial three, and 2) between trial two and trial three. The average result of these two is reported. This is referred to as the four-fold modulation test.

An extension of these analyses focused upon ignoring the transition part from one DoF to another. Recall that each profile was dynamically changing with around eleven transitions between movements (see Fig. 2). This resulted in periods of transition that are assigned to the active classes instead of no motion where the applied torque is nearly zero with a corresponding lack of EMG activity. This imposes a contradictory situation to the classifiers. Thus, we examined how rejecting these periods (assign them to no motion, using a torque threshold) would affect the classification accuracy. We investigated ignoring zone periods corresponding to approximately 8%–38% of the targeted torque level. This resembles the clinical use of prosthesis where a threshold is used on the EMG signal in order to determine when the prosthesis is inactive. In this study the no motion threshold (referred to as rejection threshold) was varied from 8% to 38% in ten equal steps.

F. Statistical Analysis

For each EMG signal type (surface and intramuscular), a two-way repeated measures analysis of variance (ANOVA) was used to compare PCC between the classifiers and different feature reduction methods. For each step of the analysis, a two-way repeated measure ANOVA (with factors EMG signals and thresholds) was also used to compare the performance of intramuscular and surface EMG and the gain of applying increased rejection thresholds. P-values less than 0.05 were considered significant. The Bonferroni-Dunn adjustment was used for multiple comparisons.

III. RESULTS

A. Four Fold Validation

1) Without Rejection Threshold: For both surface and intramuscular EMG, there was a significant difference between classifiers ($p < 0.001$) with KNN performing worse than the other four classifiers (ANN, LDA, SVMOAA and SVMOAO). When comparing the effect of dimensionality reduction, there was also a significant difference ($p < 0.001$), with PCA95 having the worst performance for both types of EMG signals. *No reduction* provided the best global result followed by SEP99 and PCA99 as illustrated in Fig. 3. However, a significant interaction was found, meaning that different classifiers were affected differently by the choice of reduction method as depicted in Fig. 4.
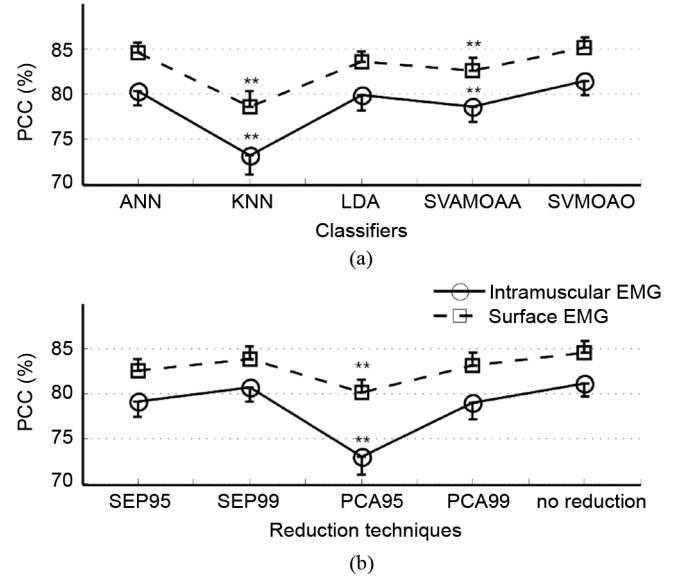

Fig. 3. Results of the four fold validation test per signal type comparing: (a) performance between different classifiers and (b) between different feature space reduction techniques. ∗∗ indicates cases where the performance is significantly worse ($p < 0.001$) than the remaining factors.
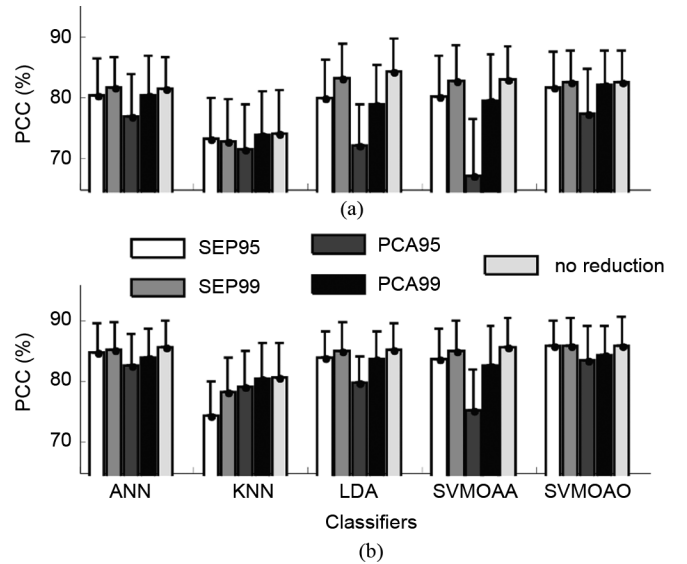

Fig. 4. Interactions between the choice of classifier versus choice of reduction method for (a) intramuscular EMG and (b) surface EMG.

Thus, for the remaining of the analysis, only three classifiers were tested (ANN, LDA and SVMOAO) with *no reduction* in the feature space.

2) With Rejection Threshold: As expected, two-way ANOVA revealed a significant difference ($p < 0.001$) between rejection thresholds up to step five corresponding to 21% of the targeted torque level. No significant difference was found between surface ($92.5 \pm 3.5\%$) and untargeted intramuscular (90.3 ± 4.7) EMG ($p = 0.13$). No difference was found between the classifiers for both types of EMG, thus Fig. 5 only presents data from the LDA classifier.
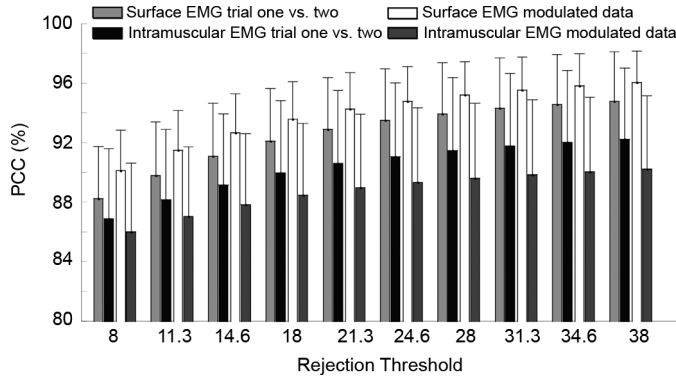
Fig. 5. Results of (a) the four fold validation test, (b) single trial test and (c) modulation test data plotted for both surface and intramuscular EMG at different rejection threshold spanning from 0% to 38% of the desire force.
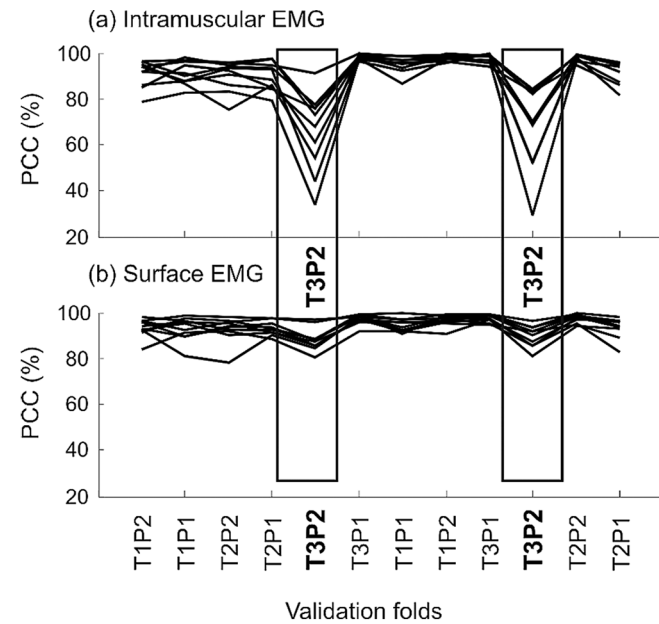

Fig. 6. Results from each fold from all four-fold validation tests shown for all subject using (a) intramuscular EMG and (b) surface EMG. (a) Note a decrease when training with part one of trial 3 and test on part two of the same trial as indicated with the rectangular. TxPy stands for testing on Trial x (1 to 3) and Part y (1 or 2).

B. Four Fold Modulation Test

As for the previous case, a significant difference was observed between the thresholds. However, there was also a significant difference between surface ($93.9 \pm 2.5\%$) and intramuscular EMG ($88.7 \pm 3.5\%$) when involving modulated data (Fig. 5), with sEMG performing better ($p = 0.005$). A significant interaction was also observed, indicating that the difference depended on the threshold value. In fact, when trained with modulated data, surface EMG increased in performance while intramuscular decreased in performance. A possible explanation is presented in Fig. 6, which depicts the classification accuracy of each fold in the three tests. We can note a decrease in performance, consistent for all subjects, at two spots corresponding to the classification of the second half of trial three.

IV. DISCUSSION

This study analyzed the effectiveness of using pattern recognition techniques for resolving simultaneous and dynamic movements and the comparison between surface and untargeted intramuscular EMG. The investigation revealed that pattern recognition can resolve simultaneous movements with considerable accuracy (up to 93%). Moreover, when tested on data that are similar in nature (nonmodulated data), surface and untargeted intramuscular EMG resulted in statistically the same performance. However, when tested on more complex data (with modulation), surface EMG outperformed intramuscular EMG. The performance of surface EMG increased when training with more complex data (modulated) as this type of data adds more information into the system, as previously shown [11], [24]. However, contrary to the observation based on surface EMG, the performance of intramuscular EMG on modulated data was poorer than on nonmodulated signals. In this case, the most prominent error occurred when training with part one of trial 1 and testing on part two of trial 3. This is most likely related to the nature of the modulation, as the modulation begins with low amplitude and low frequency and ends with higher amplitude and frequency. Surface EMG measures the global information about a contraction, while intramuscular is more selective and with the type of electrodes used in this study (wires exposed only at the tip) the recording was very selective.

Thus, as intramuscular recordings rely on the recruitment of motor units, it could be that not enough information was captured at low amplitude/frequency. This is further supported by the fact that adding the first half of trial 3 to the training set did not add the necessary information needed for classification of the more rapid changes in frequency and higher amplitude (second half of trial 3, see Fig. 6). However, the results with intramuscular recordings obtained in this study are still promising for future use of implantable electrodes, because, besides the value added in terms of potential chronic implantation, the performance is theoretically unchanged for data of similar nature (nonmodulated data). Still, more care should be taken when applying intramuscular EMG compared to surface EMG in the training phase. For example, in our case the modulated data should have contained repeated cycles of low and high amplitude/frequency in order to get a more representative training data set.

It is difficult to compare the results of this study with others, because to our best knowledge no other studies have used data as challenging in nature as the current, which were both dynamic with transitions directly between movements, and, moreover, contained simultaneously performed DoFs. All previous studies have used steady-state data in sequential movements. Nevertheless, Lorrain et al. [24] has reported a decrease in classification performance when classifying data that were semi-dynamic (a ramp followed by static contraction).

Results also showed that the rejection threshold had a significant influence on the performance up to level five, corresponding to 20% of the targeted torque level. This is reasonable as at this level the influence of background noise is less pronounced and EMG signals are easy to differentiate from noise. Nearly all commercially available prosthetic devices use a kind

of threshold on the EMG activity in order to differentiate the active state from rest. The difference between surface and intramuscular EMG was not prominent when trained with a fold validation technique on nonmodulated data mainly due to the involvement of the properties of the test data in the training set, as explained above. The results with fold validation agree with previous reports [19], [27] that compared surface and intramuscular EMG. We found a significant difference on modulated trial which was not included in previous comparisons. These authors only used steady-state EMG, where the signal is more or less stationary and thus less challenging for the classifier. Moreover, the classified movements were not performed simultaneously as in this study. Another challenge is the classification of supination/pronation which has been reported as a difficult DoF to estimate when not recording from the primary muscles (supinator and pronator, respectively) [30], [31]. This has been confirmed by a recent study [23] on force estimation using targeted intramuscular EMG with indwelling electrodes placed in the supinator m. and pronator teres m. The study showed that with this configuration, force during pronation had the highest accuracy compared to the other movements and their combinations. Although untargeted intramuscular EMG can save time on locating targeted muscle and placing electrodes in them, we believe that targeting muscles is a necessary step to take. The modulation issue discussed above might have been avoided with targeted intramuscular EMG that could capture low activities from the supinator and pronator muscles.

We compared the performance of different classifiers and found that only KNN performed significantly worse than the other four classifiers. This result extends those of previous studies [19], [32] that showed on a less complex data set that the classifier did not have a large impact on the myocontrol accuracy. Finally, we compared the effect of applying PCA and SEPCOR with different degrees of feature retention. PCA95 performed significantly worse than the other approaches. Similar performance was seen between PCA99 and SEP99, but the advantage of PCA99 (on average 21 features) is that the number of retained features was less than SEP99 (on average 48 features). It should be noted that the classifiers were affected differently by the reduction techniques. Nevertheless, there was no advantage in reducing the feature space since using the no reduction technique consistently provided the highest performance in terms of absolute value across classifiers. On the other hand, SEPCOR has the advantage of being a feature selection technique rather than a feature projection technique, such as PCA. Thus, even though PCA99 only uses 21 features, these are obtained by transformation of all the original features, whereas SEPCOR simply removes features from the original feature space. The latter approach can thus save computational time.

V. Conclusion

The novelty of this study lies in testing the ability of pattern recognition to resolve movements that were both dynamic and simultaneous and showed that the performance was acceptable but depended on the nature of the data used. Surface and untargeted intramuscular EMG had equal performance for data of similar nature, but the performance of intramuscular EMG worsened substantially for modulated data.

This study provides a theoretical assessment on how pattern recognition may resolve simultaneous and dynamic movements. We applied a four-fold validation technique to assess the performance. This type of training modality symbolizes the ideal situation with the aims: 1) to reduce the variance of the accuracy estimate and 2) to provide more training data per estimate. However, this training strategy is just a theoretical expression on how the scheme might work in practice and should be tested in real application with potential users

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Ernest Nlandu Kamavuako (M'11) received the M.S. and Ph.D. degrees in biomedical engineering from Aalborg University, Denmark, in 2006 and 2010, respectively.

He has been working as an Assistant Professor at the Department of Health Science and Technology, Aalborg University, since 2010. From 2007 to 2008, he worked as a Research Scholar at the Biomedical Department at IUPUI, Indianapolis, IN, USA. Since 2012, he has been working as a Postdoctoral Fellow at the Institute of Biomedical Engineering, University of New Brunswick, Canada. His main research interests include the use of invasive recordings in the control of upper limb prostheses, muscle recovery functions following electrical stimulation, signal processing and the application of near-infrared spectroscopy for brain-computer interface and speech processing, as well as signal processing in general.

Jakob Celander Rosenvang received the M.S. degree in biomedical engineering from Aalborg University, Denmark, in 2012.

His main research areas include design and development of control systems suitable for control of upper limb prosthesis based on both invasive and noninvasive recordings, and brain-computer interface using near-infrared spectroscopy. Since 2012, he has been working as a Consultant in Capgemini, Denmark, with focus on design and development of software suitable for use in clinical settings, e.g., Bookplan, a specialized booking and coordination system to optimize the flow in clinical settings. His main interests include signal processing and design and development of software solutions suitable for clinical use.

Ronnie Horup received the M.S. degree in biomedical engineering in 2012 from Aalborg University, Denmark.

During his studies he developed an algorithm to segment the bronchial tree in collaboration with Aalborg Hospital, in order to reduce the target volume in image-guided radiotherapy. Furthermore, he has investigated the phenomenon known as central sensitization in pain a study. Since 2012, he has been working as a Consultant at Odense University Hospital with focus on implementing sustainable solutions for the clinical environment. His main interest, however, lies in signal processing and design of software solutions clinical use.

Winnie Jensen (M'05) received the M.Sc. degree in electrical engineering and Ph.D. degree in bioengineering from the Department Health Science and Technology, Aalborg University, Denmark, in 1997 and 2001, respectively.

From 2003 to 2006, she worked as a Postdoctoral Fellow at the University of Illinois, Chicago, as a Research Associate Professor. In 2003, she was awarded an EU Marie Curie Outgoing International Fellowship. She has been working as an Associate Professor at the Department of Health Science and Technology, Aalborg University, since 2006. Her main research interests include use of implantable neural interfaces in neural prosthesis applications, and the integration of neural prosthesis applications at peripheral and cortical level.

Dr. Jensen is a member of the Society for Neuroscience.

Dario Farina (M'01–SM'09) received the Ph.D. degree in automatic control and computer science from the Ecole Centrale de Nantes, Nantes, France, and the Ph.D. degree in electronics and communications engineering from Politecnico di Torino, Torino, Italy, in 2002.

After working as an Associate Professor (2004–2008) and then Full Professor (2008–2010) at Aalborg University, Denmark, in 2010 he was appointed Full Professor and Founding Chair of the Department of Neurorehabilitation Engineering, University Medical Center Göttingen, Georg-August University, Germany, within the Bernstein Center for Computational Neuroscience. He is also the Chair for NeuroInformatics of the Bernstein Focus Neurotechnology Göttingen. His research focuses on biomedical signal processing, modeling, neurorehabilitation technology, and neural control of movement. Within these areas, he has (co)-authored more than 250 papers in peer-reviewed journals and over 300 among conference papers/abstracts, book chapters and encyclopedia contributions.

Dr. Farina is an Associate Editor of IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING.

Kevin Englehart (S'90–M'99–SM'03) received the B.Sc. degree in electrical engineering and the M.Sc. and Ph.D. degrees from the University of New Brunswick (UNB), Fredericton, NB, Canada, in 1989, 1992, and 1998, respectively.

He is currently the Director of the Institute of Biomedical Engineering at UNB. His research interests include neuromuscular modeling and biological signal processing using adaptive systems, pattern recognition, and time-frequency analysis.

Dr. Englehart is a Registered Professional Engineer, and a member of the IEEE Engineering in Medicine and Biology Society, the International Society of Electrophsiology and Kinensiology, and the Canadian Medical and Biological Engineering Society.