A Proportional Control Scheme for High Density Force Myography

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I. ABSTRACT

***Objective*. Force Myography (FMG) has been shown to be a potentially higher accuracy alternative to electromyography for pattern recognition based prosthetic control. Classification accuracy, however, is just one factor that affects the usability of a control system. Others, like the ability to start and stop, to coordinate dynamic movements, and to control the velocity of the device through some proportional control scheme can be of equal importance. To impart effective fine control using FMG-based pattern recognition, it is important that a method of controlling the velocity of each motion be developed. *Methods.* In this work force myography data were collected from 14 able bodied participants and one amputee participant as they performed a set of wrist and hand motions. The offline proportional control performance of a standard mean signal amplitude approach and a proposed regression-based alternative was compared. The impact of providing feedback during training, as well as the use of constrained or unconstrained hand and wrist contractions, were also evaluated. *Results.* It is shown that the commonly used mean of rectified channel amplitudes approach commonly employed with electromyography does not translate to force myography. The proposed class-based regression proportional control approach is shown significantly outperform this standard approach (ρ<0.001), yielding a R^2 correlation coefficients of 0.837 and 0.830 for constrained and unconstrained forearm contractions, respectively for able bodied**

participants. No significant difference (ρ = 0.693) was found in R^2 performance when feedback was provided during training or not. The amputee subject achieved a classification accuracy of 83.4±3.47% demonstrating the ability to distinguish contractions well with FMG. In proportional control the amputee participant achieved an R^2 of of 0.375 for regression based proportional control during unconstrained contractions. This is lower than the unconstrained case for able-bodied subjects for this particular amputee, possibly due to difficultly in visualizing contraction level modulation without feedback. This may be remedied in the use of a prosthetic limb that would provide real-time feedback in the form of device speed. *Conclusion.* A novel class-specific regression-based approach is proposed for multi-class control is described and shown to provide an effective means of providing FMG-based proportional control.

I. INTRODUCTION

Myoelectric powered prostheses use information from one or more surface electromyography (EMG) sensors to estimate intent from a user's muscle contractions. Clinically, this is most commonly accomplished using two electrodes located over a pair of antagonist muscles. A form of direct control is employed in these systems whereby the velocity of the terminal device is driven proportionally to the intensity of contraction under an EMG site or the difference between two agonist / antagonist sites [1], [2].

In pattern recognition-based myoelectric control, multiple sensors are used to train a classifier [3] or a regression based model [4] using features calculated from raw EMG signals [5], [6]. Decades of research have now resulted in the emergence of a commercial pattern-recognition based myoelectric control system [7].

Early studies based on measurement of "muscle bulge"[8] employed a custom Hall effect transducer as an alternative to EMG electrodes. Although this described measuring muscle geometry changes rather than force or pressure, the elastic properties of the sensors themselves and of the muscle yielded measurements that are closely related to skin-socket pressure. Kenney *et al.* investigated range of the signal; the effects of external disturbance, sensitivity to sensor placement and finally the ability of subjects to control the magnitude of the signal, measured using a series of tracking tasks. More recent work has employed arrays of force sensors coupled with pattern recognition based methods for prostheses control [9]–[11]. In these studies, the socket-skin interface pressures resulting from muscle deformation has been referred to as force myography (FMG).

Many types of force sensors have been considered, ranging from inexpensive and readily available force sensing resistors (FSRs) [10], [12]–[14] to high density grids of pressure sensitive elements [11], pneumatic pressure based designs [15], and optical fiber based sensors [16].

High classification accuracies have been reported for both low density [10], [12] and high density [11] force sensing devices; with able-bodied participants [11], [12], amputees [17], and stroke patients [18]. FMG-based control has been implemented using support vector machines (SVM) [12], [13], [19], linear discriminant analysis (LDA) [11], and extreme learning machine (ELM) based classifiers [20] as well as regression based methods [21]. The classification performance of FMG has also been evaluated in both offline [11], [19], [22] and real-time [23] tests.

High classification accuracy alone, however, does not ensure a functional control system. For instance, recently, little correlation was found between classification accuracy and device usability metrics for EMG based systems [24], [25], [26]. Other factors, such as robust proportional control, are critical for functional use. In order to properly evaluate the viability of FMG as a usable control input for pattern-recognition based prosthetic control, it is therefore necessary to first develop a suitable proportional control algorithm [27].

The speed of a prosthetic degree of freedom may be controlled proportionally, using an estimate of the effort being exerted by the user, or discretely (as an on/off switch). On/off, or bang-bang control, allows for the manipulation of a degree of freedom of a prosthesis with only one set speed. Once a contraction is identified to be above or below a given threshold, the motor of the device is correspondingly turned on or off. The limitation of a single set speed, however, has been shown to negatively impact gross manipulation as well as fine control [27]. The inclusion of proportional control has been shown to improve target tracking in multi-channel EMG pattern recognition systems [27] and has become a common feature of commercially available prostheses [28]. It follows that a similar inclusion should also improve the function of classification-based FMG controllers.

FMG has been shown to be capable of predicting grip strength [21] and individual finger forces [14]. Wininger et al. [22] found high ($r>0.89$) correlation between a rectified sum of FSR sensor values and grip force. This approach, however, has not yet been shown to be applicable to other classes of motion. Castellini et al. [19] were able to predict forces exerted during finger flexion/extension and abduction/adduction using two radial basis function SVM regressors. A similar approach may be applicable to generalize to a variety of classes of motion.

Unlike some conventional myoelectric control approaches, classification-based control systems do not intrinsically include a method of determining proportional control. Instead, classifiers are paired with a proportional control estimator. Due to the inclusion of multiple EMG sensors, however, and the lack of direct one-to-one mappings, the derivation of a meaningful proportional control signal becomes less intuitive. One commonly employed method calculates the average mean absolute value (MAV) of all EMG channels used for pattern recognition [28]. This estimator has been shown to perform adequately because the overall level of EMG activity tends to increase with contraction intensity across multiple classes. More refined approaches for pattern recognition proportional control have been developed which scale the proportional control output using class specific gains [30] to allow for a full dynamic range of control velocities. Both approaches benefit from the fact that the average MAV of EMG increases monotonically with contraction intensity. Fig. 1 shows an example of this, including the MAVs for 8 channels of EMG, the visual target used to guide the user's level of effort, and the average value of the MAV of all channels (with an R^2 correlation coefficient of 0.938). Fig. 2 shows several representative channels of FMG, a visual target used to guide the user's intensity of contraction, and the mean signal amplitude (MSA) of all FMG channels, an analogous proportional control signal to MAV for EMG based systems (with an R^2 correlation coefficient of 0.0129), and demonstrates that signal amplitudes may increase, decrease, or remain constant with increasing effort. These differing responses in pressure distributions can be attributed to some muscles bulging outward during contractions while others retract, creating areas of decreased pressure against the cuff.

Another difference between the two sensor types is that each FMG sensor possesses some amount of pre-load applied by the supporting socket (even when at rest) which may vary depending on limb position, how tightly it is attached to the arm, and socket loading.

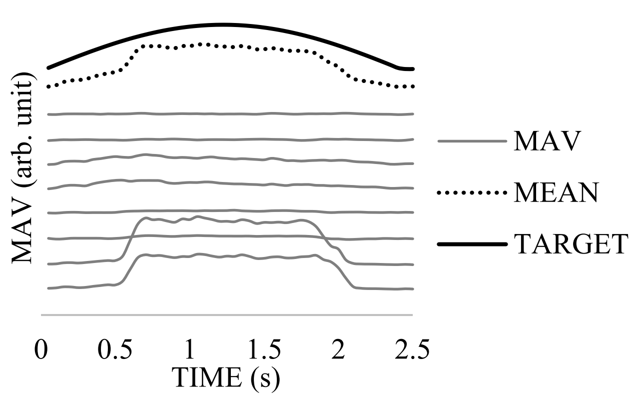

Fig. 1. EMG MAV proportional tracking with respect to a half-cycle of a sinusoidal visual target. Individual sensor MAV responses and the mean are shown.

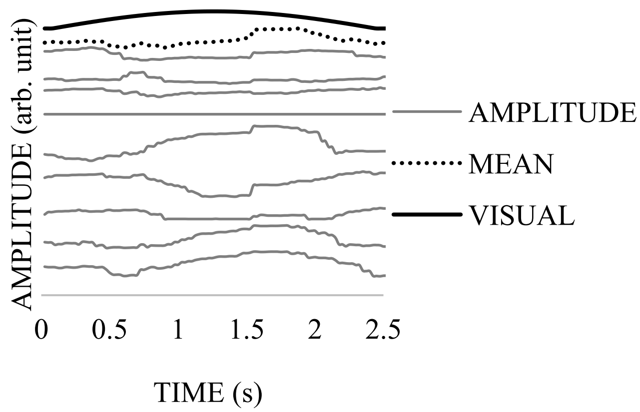

Fig. 2. FMG proportional tracking with respect to a half cycle of a sinusoidal visual target. Individual sensor amplitude responses and the mean response are shown.

These factors present barriers to reliable FMG-based proportional control. The focus of this investigation was therefore to examine the nature of FMG in response to varying contractions intensities, and to design a multi-class proportional control algorithm designed to accommodate for these factors for use in an upper limb prosthetic control system making use of commonly used classes of wrist and hand motion.

II. Methods

A. *Experimental Setup*

Fourteen normally limbed participants aged 32.1±10.3 years were recruited to perform a virtual target following task. This study was approved by the University of New Brunswick's Research Ethics Board (REB # 2015-133) in accordance with the Canadian Tri-Council Policy Statement regarding ethical conduct for research involving humans. As a preliminary case study, additional data were collected from an amputee participant with an acquired transradial limb loss (male, 25 years old, amputation 9 cm distal to elbow).

The experiment was conducted with participants seated in a chair equipped with a hand restraint connected to a six degree-of-freedom load cell. The chair also contained an elbow and wrist rest, along with a wrist restraint as shown in Fig. 3 to limit any unnecessary motion of the arm in the constrained trials.

All visual prompts and data recording was accomplished using a custom MATLAB™ graphical user interface [31] displayed directly in front of participants on a large screen.

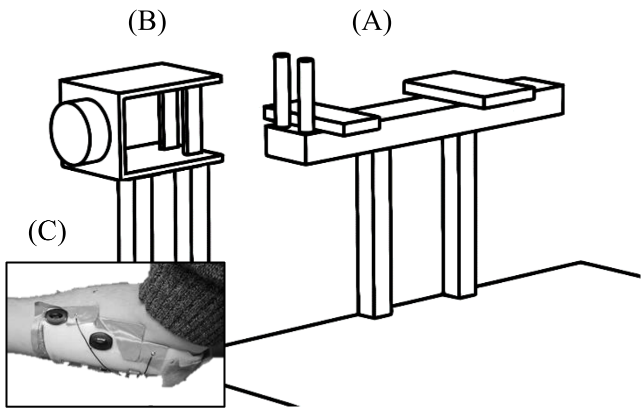

Fig. 3. The arm rest (A) and load cell apparatus (B) on the data collection chair platform. Inset: a photo of the cuff attached to the forearm (C).

B. Data Acquisition

High-Density FMG (HD-FMG)

A high-density pressure sensitive grid of 16x24 sensor elements was used, provided by Smart Skin Technologies (Fredericton, New Brunswick, Canada). This sensor is similar to the sensor grid used in 2016 by Radmand et al., [11], but with higher spatial resolution. Three sensor arrays were adhered to a thermoset plastic cuff and secured to the proximal forearm. As shown in Fig. 3, there was often a portion of the forearm left uncovered by the sensors; this was a side-effect of using a single re-sizeable cuff to collect data from participants with a range of forearm circumferences. Data sampling was performed at 15 Hz on the board provided by Smart Skin Technologies and was transmitted to a PC via Bluetooth.

Torque Signal

The torque exerted by the user in each recorded degree of freedom, in all conditions where this was possible, was measured using a six degree-of-freedom load cell (ATI F/T Gamma, ATI Industrial Automation), sampled at 1000 Hz using a Measurement Computing data acquisition board which was connected to the data collection PC via a USB cable.

C. Data Collection Procedure

Participants were seated comfortably in the chair, and the HD-FMG cuff was placed on their right forearm as shown in Fig. 3 (with columns of sensors oriented parallel to the forearm and rows of sensors spanning the circumference of the forearm).

Participants were instructed to follow on-screen prompts, matching the pattern and intensity of their contractions to a moving visual target. The type of motion and target effort level were displayed on a screen and participants were instructed to match it as closely as possible.

The suitability of constrained or unconstrained testing conditions with normally limbed subjects has been debated for EMG control [32], and the presence or absence of constraint has been shown to affect the performance of EMG-based control [4]. To test this comparison using FMG, the c*onstrained without feedback* and the *unconstrained (without feedback)* cases were compared for the no motion, flexion, extension, pronation, and supination classes (those that were subject to constraint in the apparatus). Three different constraint conditions were tested:

Constrained without feedback: Participants were prompted to gradually increase and then decrease the intensity of their contractions for each of the classes of motion. No feedback about their achieved intensity level was given, and participants were instructed to only exert themselves to approximately 60% of their maximum voluntary contraction (MVC).

Constrained with feedback. The same procedure was followed as above, however participants were given real-time feedback about their contraction intensity. Before each trial, an MVC was recorded for each of the active classes of motion and used to normalize their cursor. The target was then scaled to 60% of their MVC and visual feedback of their exertion, as measured by the load cell, was provided in real-time.

Unconstrained (without feedback). Participants repeated the *Constrained without Feedback* protocol, but with their hand freed from the arm restraints and load cell. For the amputee subject this was the only test condition which was collected.

The order of motion classes and the constraint conditions were randomized for each participant. Prior to testing, participants were coached on how to perform each of the motions in a way that was as separable and repeatable as possible. Ten trials were conducted for each of the constraint conditions.

D. Data Processing

An SVM classifier was used as described in [11] to determine class decisions. The FMG is a regular, unipolar waveform and it has been shown not to require the extraction of features for fine waveform characterization [11] as is required of EMG [33]. Consequently, the sensor output value was the only feature used for classification.

A novel proportional control algorithm for HD-FMG was developed, with processing steps as follows.

E. Data Preparation

Training data were thresholded using the visual target. Data corresponding to a visual target value below 10% of the maximum visual target range were re-labeled as no-motion for the classifier target and zero for the regression target[1].

Prior to training, all data were scaled by dividing by the largest sensor value present in the complete training set.This allowed the dynamic range of the range of the sensors to be effectively utilized. The visual target and torque targets were also resampled at 15 Hz to match the FMG data.

Classifier Training and Testing: An SVM classifier [34] with linear kernel was trained and tested using the thresholded class targets and normalized data. A leave-one-out approach was used: training on all but one repetition and testing on the withheld repetition and repeating this process so that each repetition was tested. The overall accuracy is the average of that on each test set.

Regression Training and Testing: For each of the classes of motion, an SVM regression model [4] with linear kernel was trained using the thresholded regression targets and normalized data. As with classification, leave-one-out approach was employed in training and testing,

For both classification and regression SVM models the cost parameter was selected by randomly selecting one repetition from each participant to test the model, which was trained using other repetitions. The cost parameter was varied on a logarithmic scale from 10^{-5} to 10^{5}. This was done for classification and regression models separately, but the optimal cost parameter was found to be 0.1 for both (averaged across all subjects). Further tuning of the cost parameter search using the training data did not improve the average classification or regression performance. It is possible that better performance could have been achieved if parameter

[1] The rationale for relabeling data samples less than 10% is to augment the "no motion" training data to include these data. This will generate classifiers and regressors that identify these data with no motion instead of an active class. If this is not done, any low-level activity (perhaps due to unintended motion) will be assigned to an active class, which is a costly error in prosthesis control.

selection was performed individually for each subject, but this would not be practical to perform in a clinical situation.

F. Data Analysis

The data were split into each of the ten total collected repetitions for analysis. First the classification accuracy was calculated for testing with each individual repetition and training with all remaining repetitions. This resulted in improving classification accuracy over the first three repetitions before attaining a consistent mean classification accuracy across all participants for repetitions four through ten. This was attributed to the cuff settling into a stationary position on the arm, and to a learning effect as the participants became familiarized with the motions being conducted.

For these seven remaining repetitions, all performance metrics calculated in this paper were from seven-fold cross validation in which each individual repetition was tested against a model trained using the remaining six repetitions.

G. Channel Reduction

Using many FMG sensors (384 in this case) may improve redundancy of information, but it also increases computation time and the likelihood of classifier and regression model overfitting. Consequently, channel row reduction was evaluated in this work. Full columns of sensors were preserved to ensure the inclusion of pressure information around the circumference of the arm, while different numbers of active rows of sensors were evaluated.

Performance was evaluated using both classification accuracy and regression R^2 correlation coefficients for varying numbers of sensor rows, from 1 to all 16. Groupings were constrained to adjacent rows to emulate potential FMG device designs which would benefit from tighter clustering of sensors. For each number of rows, all possible combinations of adjacent rows or sensors were evaluated.

H. Statistics

Results for this study were assessed for normality and then a student t-test ($p<0.05$) was conducted to determine significance. In the event of non-normal distribution, a Mann-Whitney U test was conducted ($p<0.05$).

III. Results

A. Channel Reduction

Fig. 4 visualizes how the inclusion of additional rows of sensors affected the classification accuracy, and regression R^2 correlation coefficient. The horizontal dotted lines show the performance when all rows of sensors were included.

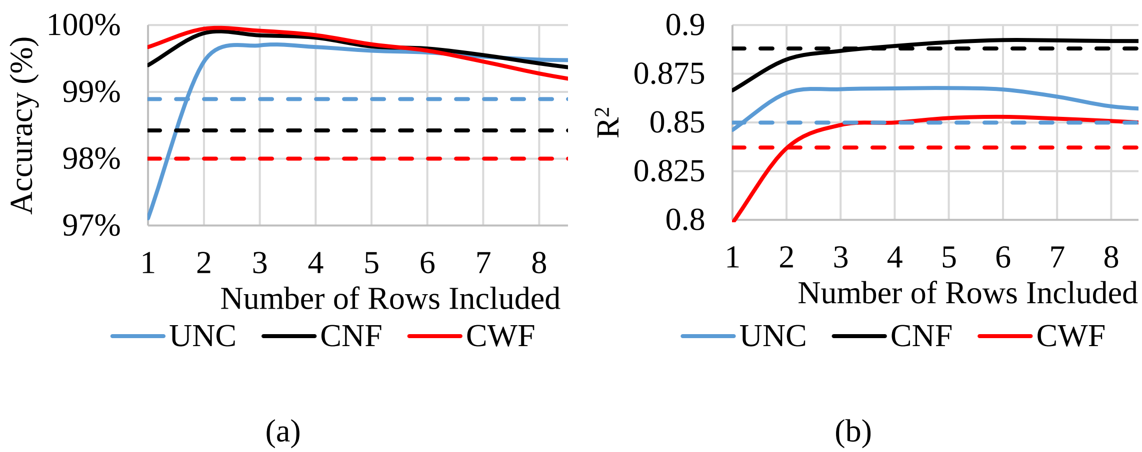

Fig. 4. (a) Total classification accuracy and (b) R^2 performance by number of rows of sensors. Horizontal dotted lines denote the corresponding performance when all rows are included. UNC = unconstrained (without feedback), CNF = constrained (with feedback), CWF = constrained (without feedback).

Total classification accuracy increases with the inclusion of two and three rows of sensors, and then gradually decreases with additional rows (Fig. 4 a). Regression R^2 performance also plateaus after three rows but continues to rise slightly until six rows are included (Fig. 4 b).

B. Force Feedback During Training

The torque output of the wrist was recorded using a tri-axial load cell during the constrained condition; real-time feedback of effort was provided to assist in following the visual target. While this is impractical for clinical use with amputees (without the use of bilateral training), the measured torque was used as a means of evaluating the impact of real-time exertion level feedback and as a baseline comparison for the visual training approach in the constrained condition. Both classification accuracy and regression R^2 correlation coefficients failed a test of normality, and a corresponding Mann-Whitney test found no significance difference in classification accuracy when feedback was provided or not, ($\rho = 0.693$). The R^2 regression performance was significantly better when no feedback was provided ($U=2477$, $\rho=0.001$). Regression performance may have been worse with feedback because participants tended to over-correct for small errors.

C. *Regression Target Type*

During training and testing, the subjects followed a visual target to guide their exertion level. If real-time feedback was provided, it was with the use of the torque sensor. An interesting question is: what the relative performance of the regression is if the visual target (what they were asked to follow) is used as the training/testing target, as compared to torque target (what they actually produced). When feedback was provided, a Mann-Whitney test indicated that the R^2 correlation coefficient was greater when the torque target was used (Mdn=0.900) than when the visual target was used (Mdn=0.822), $U=1918$, $\rho<0.001$. When no feedback was provided, the R^2 correlation coefficient was again greater when the torque target was used (Mdn=0.899) than when the visual target was used (Mdn=0.848), $U=2166$, $\rho<0.001$.

D. *Constraint Conditions*

Mann-Whitney tests were conducted to compare the classification accuracy and R^2 correlation coefficient for the constrained versus unconstrained conditions. Contrary to results reported using EMG [4], neither classification accuracy, ($U=3109$), ($\rho=0.018$) nor regression R^2 correlation coefficient ($U=3153$), ($\rho =0.234$) were significantly different between the two constraint types. The median classification accuracy for both conditions was 100%.

E. Proportional Control

The use of a regression based approach toward proportional control also provided more consistent offline performance both between classes, as well as between participants, as visualized in **Error! Reference source not found.**5 in which the visual target, the mean proportional control value, as well as the distribution of proportional control values among all trials for all participants represented as a 95% confidence interval.

The results presented by Wininger et al. [22], which demonstrated a high correlation between a rectified sum of FSR values and grip force is corroborated by the MSA results for power grip shown in **Error! Reference source not found.**5. The MSA approach, however, fails to accurately track other contraction types, such as the wrist articulations.

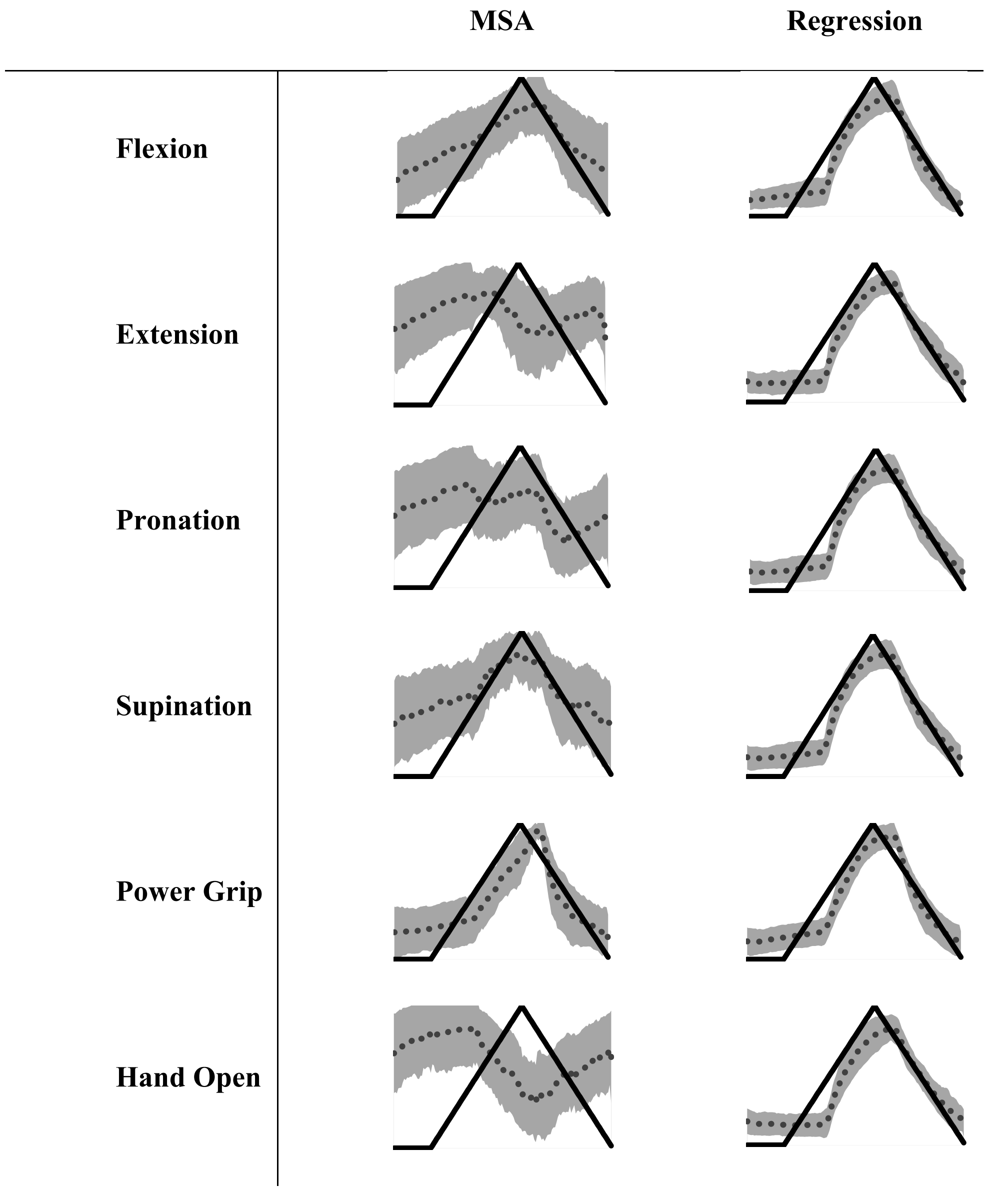

Fig. 5. Class-specific qualitative performance of MSA and regression to predict effort. Including the visual target value (solid black), the mean proportional control (dotted), and the 95% CI (grey) for all participants and all trials.

The performance of the MSA and regression proportional control approaches are shown in Fig. 6. for the six unconstrained motions and four constrained motions.

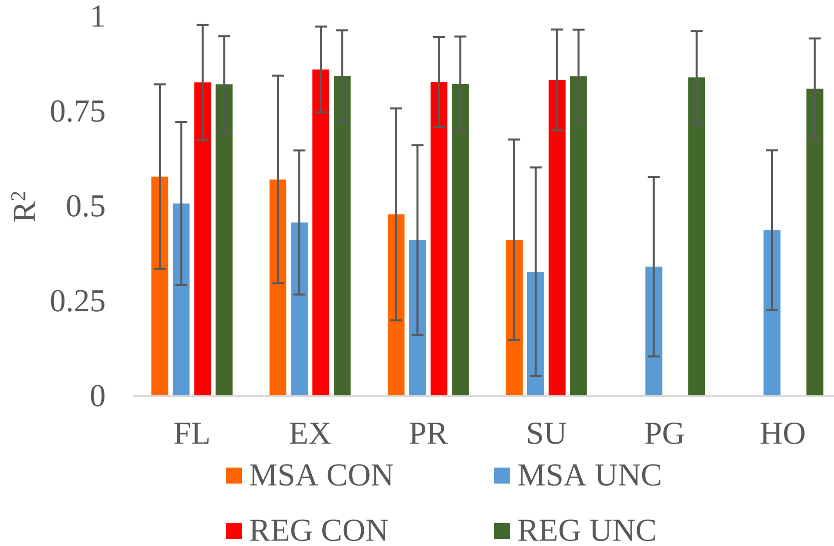

Fig. 6. Class-specific proportional control R^2 for constrained and unconstrained conditions with standard deviation. MSA=mean signal amplitude, REG= regression, CON=Constrained, UNC=Unconstrained.

F. Classification and Regression Accuracy

Table 1 shows a confusion matrix of the classification performance after row reduction (to three rows) and thresholding for the *constrained without feedback* condition. The comparable regression R^2 correlation coefficients were 0.827, 0.861, 0.828, and 0.833 for the no motion, flexion, extension, pronation, and supination classes, respectively.

TABLE 1
Classification accuracy confusion matrix, in percent, for constrained without feedback trials. Classes include no motion (NM), flexion (Fl), extension (Ex), pronation (Pr), and supination (Su).

		TEST				
		NM	**Fl**	**Ex**	**Pr**	**Su**
TRAIN	**NM**	100.0	0.7	0.6	0.8	1.3
	Fl	0.0	99.3	0.0	0.0	0.0
	Ex	0.0	0.0	99.4	0.0	0.1
	Pr	0.0	0.0	0.0	99.2	0.0
	Su	0.0	0.0	0.0	0.0	98.6

The classification results for the unconstrained condition are summarized in **Error! Reference source not found.**2. The regression-based proportional control R^2 correlation coefficients for the unconstrained condition were 0.822, 0.844, 0.823, 0.844, 0.840, and 0.810 for flexion, extension, pronation, supination, power grip, and hand open, respectively.

Table 2: Classification accuracy confusion matrix, in percent, for unconstrained trials. Classes include No motion(NM), flexion (Fl), extension (Ex), pronation (Pr), supination (Su), power grip (PG), and hand open (HO).

		TEST						
		NM	Flex	Ext	Pro	Sup	PG	HO
TRAIN	NM	100	1.4	0.0	3.2	0.1	1.0	0.0
	Flex	0.0	98.6	0.0	0.0	0.0	0.0	0.0
	Ext	0.0	0.0	99.7	0.0	0.0	0.0	0.0
	Pro	0.0	0.0	0.2	96.7	0.0	0.0	0.1
	Sup	0.0	0.0	0.2	0.0	99.7	0.4	0.0
	PG	0.0	0.0	0.0	0.0	0.0	98.6	0.0
	HO	0.0	0.0	0.0	0.0	0.1	0.0	99.8

The amputee subject achieved a total classification accuracy of 83.42±3.47% and a mean active classification accuracy of 85.60%. The mean R^2 correlation coefficient for the regression-based method achieved an R^2 of 0.375.

IV. Discussion

In this work, two different proportional control algorithms, MSA and regression, were compared for pattern-recognition based FMG control. A novel class-specific regression proportional control with multi-class FMG-based pattern recognition was proposed in this work. The commonly used MSA approach was shown to be ineffective for multi-class control of the wrist and hand. The proposed method obtained significantly better R^2 regression correlation coefficients ($\rho<0.001$) of 0.837 for constrained trials and 0.830 for unconstrained trials, whereas the MSA based proportional control resulted in values of 0.510 and 0.414, respectively.

Providing force feedback during collection was found to have no significant effect on classification accuracy but did reduce regression R^2 correlation coefficient ($\rho=0.001$). This may have been the result of participants performing small over-corrections in the contractions while attempting to more closely follow the torque target. Training the regression models using a torque target was shown to provide improvement over the use of a visual target ($\rho<0.001$). Use of the torque measurement yielded a mean R^2 regression coefficient of 0.879, whereas training using the visual prompt produced a R^2 with a mean of 0.847 (96.4% of that of the torque target). These results indicate that there is little benefit to having a true torque signal for the purpose of either providing user feedback during training, or for use as a target for training a regression model. This is promising as the condition without feedback and with no torque signal available is more clinically relevant as these measurements are not available for amputees. It does indicate however that there is an opportunity to improve the visual training process more suitable regression algorithms or novel training methods.

No significant difference was found in the R^2 correlation coefficient between the two constraint conditions. This consistent performance regardless of constraint condition is promising as this control approach should translate more readily to amputee subjects, regardless of whether their muscular effort more closely resembles constrained or unconstrained contractions, however further investigation with amputee participants is required to confirm this.

While the information present in the full set of sensors was found to be redundant through the process of sensor reduction, this approach also appears to be resilient to overfitting as there was a decrease of less than 2% in classification accuracy and R^2 when all rows of sensors were used when compared to when only three were used.

The proposed proportional control system involves a two-step prediction process, first using the data to predict an active class using an SVM classifier, then implementing class-specific proportional control estimation using a regression model. This additional layer of complexity may be avoided if both steps were handled by a regression model as with EMG based regression [4] however, while a purely regression based approach has been evaluated in a controlled environment it has yet to be proven in a commercially available prosthesis. This approach combines the clinically proven approach of using classification-based pattern recognition to derive control signals with an improved level of proportional control.

This current work, while constrained to offline investigation, focused on understanding the challenges of using FMG for proportional control, and demonstrating the efficacy of the class-specific regression approach. The next stage must address real-time ‘user in the loop’ control. Additionally, to demonstrate the practical value for FMG-based control, the effects of dynamic loading and external perturbations (such as leaning on a table) must be evaluated. This will necessitate the fabrication and fitting of custom sockets for each patient to accurately reflect the clinical potential of such systems. Additional logic, such as rejection [35], will likely be required to accommodate the introduction of unknown pressure patterns.

The amputee data supports the hypothesis that FMG is a functional alternative to EMG for upper limb prosthetic control via pattern recognition from a classification accuracy perspective. The regression based proportional control algorithm did not perform as well on the amputee data, only achieving a mean R^2 correlation with the visual target of 0.375. This is lower than the unconstrained case for able-bodied subjects (R^2=0.83) for this particular amputee, possibly due to difficultly in visualizing contraction level modulation without feedback. This may be remedied in the use of a prosthetic limb that would provide real-time feedback in the form of device speed**.**

V. CONCLUSION

A control scheme has been developed for HD-FMG pattern recognition which accounts for the complex nature of the pressure profiles during varying contraction intensity. It is shown to be generalizable across wrist and hand motions in constrained and unconstrained conditions. This method employs SVM classification to determine the active class and then uses class specific regression models to derive the proportional control. This system has the advantage of being based on a classification-based control system which has been proven to be very robust. Supplementing FMG pattern recognition with regression based proportional control should significantly improve the real-time usability of such an approach, which is currently under investigation.

Earlier comparisons of FMG classification accuracy between the intact arm and residuum of amputee participants found a classification accuracy when using their residual limb, compared to for their intact limb. This reduction in accuracy for the FMG based approach is attributed to an absence of anatomical features and muscle tone and volume [10]. This is a consistent reduction in classification accuracy when compared to EMG systems being 15% higher in amputees using their intact arm than when using their residuum [36]. The FMG system tested in this study was observed to provide similarly high classification accuracy for able bodied and amputee participants. The class-based regression proportional control algorithm developed in this study using data from able-bodied participants performed exceptionally well. The proportional control performance with the amputee was not as robust, suggesting that a better training protocol is required which provides real-time feedback of contraction intensity. Clearly more limb deficient subjects are required for a definitive conclusion. The range of variations in musculature and motor pathways is diverse in limb deficient individuals, so this will require extensive experimentation.

The scope of this investigation was also limited to offline analysis of recorded data. This investigation was undertaken with the goal of developing a proportional control approach for use with HD-FMG to compare against an EMG based pattern recognition system in a real-time performance comparison.

VI. ABBREVIATIONS

EMG: Electromyography; FMG: Force Myography; SVM: Support vector machine; LDA: Linear discriminant analysis; ELM: Extreme learning machine; MAV: Mean absolute value; MSA: Mean signal amplitude; Mdn: Median; MVC: Maximum voluntary contraction; R^2: R^2 correlation coefficient.

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VII. REFERENCES

[1] H. H. Sears and J. Shaperman, "Proportional myoelectric hand control: an evaluation.," *Am. J. Phys. Med. Rehabil.*, vol. 70, no. 1, pp. 20–28, Feb. 1991.

[2] S. C. Jacobsen, D. F. Knutti, R. T. Johnson, and H. H. Sears, "Development of the Utah Artificial Arm," *IEEE Trans. Biomed. Eng.*, vol. BME-29, no. 4, pp. 249–269, 1982.

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

[4] A. Ameri, E. N. Kamavuako, E. J. Scheme, K. B. Englehart, and P. A. Parker, "Support Vector Regression for Improved Real-Time , Simultaneous Myoelectric Control," vol. 22, no. 6, pp. 1198–1209, 2014.

[5] D. Tkach, H. Huang, and T. A. Kuiken, "Study of stability of time-domain features for electromyographic pattern recognition.," *J. Neuroeng. Rehabil.*, vol. 7, no. 1, p. 21, 2010.

[6] J. Liu, "Feature dimensionality reduction for myoelectric pattern recognition: A comparison study of feature selection and feature projection methods," *Med. Eng. Phys.*, vol. 36, no. 12, pp. 1716–1720, 2014.

[7] "COAPT." [Online]. Available: http://www.coaptengineering.com/.

[8] L. P. J. Kenney, I. Lisitsa, P. Bowker, G. H. Heath, and D. Howard, "Dimensional change in muscle as a control signal for powered upper limb prostheses: A pilot study," *Med. Eng. Phys.*, vol. 21, no. 8, pp. 589–597, 1999.

[9] D. Yungher and W. Craelius, "Discriminating 6 Grasps Using Force Myography of the Forearm," 2003.

[10] E. Cho, R. Chen, L. Merhi, Z. G. Xiao, and B. Pousett, "Force Myography to Control

Robotic Upper Extremity Prostheses : A Feasibility Study," *Front. Bioeng. Biotechnol.*, vol. 4, no. March, pp. 1–12, 2016.

[11] A. Radmand, E. Scheme, and K. Englehart, "High density force myography: A possible alternative for upper-limb prosthetic control," *JRRD*, vol. 53, no. 4, pp. 443–456, 2016.

[12] N. Li, S. Wei, M. Wei, and B. Liu, "Hand Motion Recognition Based on Pressure Distribution Maps and LS-SVM," no. Icmc, pp. 1027–1031, 2014.

[13] C. Castellini and V. Ravindra, "A wearable low-cost device based upon Force-Sensing Resistors to detect single-finger forces," *Int. Conf. Biomed. Robot. Biomechatronics*, pp. 199–203, 2014.

[14] A. Kadkhodayan, X. Jiang, and C. Menon, "Continuous Prediction of Finger Movements Using Force Myography," *J. Med. Biol. Eng.*, no. July, 2016.

[15] R. L. Abboudi, C. A. Glass, N. A. Newby, J. A. Flint, and W. Craelius, "A Biomimetic Controller for a Multifinger Prosthesis," *IEEE Trans. Rehabil. Eng.*, vol. 7, no. 2, pp. 121–129, 1999.

[16] E. Fujiwara, Y. T. Wu, M. F. M. Santos, E. A. Schenkel, and C. K. Suzuki, "Development of an Optical Fiber FMG Sensor for the Assessment of Hand Movements and Forces," *2015 IEEE Int. Conf. Mechatronics*, 2012.

[17] S. L. Phillips and W. Craelius, "Residual Kinetic Imaging: A Versatile Interface for Prosthetic Control," *Robotica*, vol. 23, no. 3, pp. 277–282, 2005.

[18] C. Menon, "Force Myography for Monitoring grasping in individuals with stroke with Mild to Moderate Upper-extremity impairments : a Preliminary investigation in a controlled environment," vol. 5, no. July, pp. 1–11, 2017.

[19] C. Castellini and R. Koiva, "Using a High Spatial Resolution Tactile Sensor for Intention

Detection.," *IEEE Rehabil. Robot.*, pp. 1–7, 2013.

[20] Z. G. Xiao, A. M. Elnady, and C. Menon, "Control an Exoskeleton for Forearm Rotation Using FMG," vol. 1, pp. 591–596, 2014.

[21] N. Jaquier, C. Castellini, and S. Calinon, "Improving Hand and Wrist Activity Detection Using Tactile Sensors and Tensor Regression Methods on Reimannian Manifolds," *MEC17 - A Sense What's to Come*, pp. 78–81, 2017.

[22] M. Wininger, N.-H. Kim, and W. Craelius, "Pressure Signature of Forearm as Predictor of Grip Force.," *J. Rehabil. Res. Dev.*, vol. 45, no. 6, pp. 883–892, 2008.

[23] Z. G. Xiao and C. Menon, "Towards the development of a wearable feedback system for monitoring the activities of the upper-extremities.," *J. Neuroeng. Rehabil.*, vol. 11, p. 2, 2014.

[24] B. Lock, K. B. Englehart, and B. Hudgins, "Real-time myoelectric control in a virtual environment to relate usability vs. accuracy," *Proc. 2005 MyoElectric Control. Prosthetics Symp.*, pp. 17–20, 2005.

[25] L. J. Hargrove, E. J. Scheme, K. B. Englehart, and B. S. Hudgins, "Multiple binary classifications via linear discriminant analysis for improved controllability of a powered prosthesis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 1, pp. 49–57, 2010.

[26] B. A. Lock, *Design and Interactive Assessment of Continuous Multifunction Myoelectric Control Systems*, no. September 2005. Fredericton, 2003.

[27] A. M. Simon, K. Stern, and L. J. Hargrove, "A comparison of proportional control methods for pattern recognition control," *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, pp. 3354–3357, 2011.

[28] A. Fougner, O. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. A. Parker, "Control of upper

limb prostheses: Terminology and proportional myoelectric control - a review," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 20, no. 5, pp. 663–677, 2012.

[29] S. S. Mostafa, M. Ahmad, and M. A. Awal, "Clench force estimation by surface electromyography for neural prosthesis hand," *2012 Int. Conf. Informatics, Electron. Vision, ICIEV 2012*, pp. 505–510, 2012.

[30] E. Scheme, B. Lock, L. Hargrove, W. Hill, U. Kuruganti, and K. Englehart, "Motion normalized proportional control for improved pattern recognition-based myoelectric control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 1, pp. 149–157, 2014.

[31] E. Scheme and K. Englehart, "A flexible user interface for rapid prototyping of advanced real-time myoelectric control schemes," *MyoElectric Control. Prosthetics Symp.*, pp. 13–16, 2008.

[32] M. B. Kirstoffersen, A. Franzke, A. Murgia, R. Bongers, and C. K. Van Der Sluis, "Influence of a Transradial Amputation on Neuromuscular Control of Forearm Muscles," *MEC17 - A Sense What's to Come*, p. 113, 2017.

[33] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Med. Eng. Phys.*, vol. 21, pp. 431–438, 1999.

[34] M. A. Oskoei, S. Member, H. Hu, and S. Member, "Support Vector Machine-Based Classification Scheme for Myoelectric Control Applied to Upper Limb," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 8, pp. 1956–1965, 2008.

[35] E. J. Scheme, B. S. Hudgins, and K. B. Englehart, "Confidence-based rejection for improved pattern recognition myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 6, pp. 1563–1570, 2013.

[36] G. Li and T. A. Kuiken, "EMG pattern recognition control of multifunctional prostheses by transradial amputees," *Proc. 31st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. Eng. Futur. Biomed. EMBC 2009*, pp. 6914–6917, 2009.

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