FMG vs EMG: A Comparison of Usability for Real-time Pattern Recognition Based Control

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Abstract—Objective: **Force Myography (FMG), which measures the surface pressure profile exerted by contracting muscles, has been proposed as an alternative to electromyography (EMG) for human-machine interfaces. Although FMG pattern recognition-based control systems have yielded higher offline classification accuracy, but comparatively few works have examined the usability of FMG for real-time control. In this work, we conduct a comprehensive comparison of EMG and FMG-based schemes using both classification and regression controllers.** ***Methods:*** **Twenty participants performed a two degree of freedom Fitts' Law-style virtual target acquisition task using both FMG- and EMG-based classification and regression control schemes. Performance was evaluated based on the standard Fitts' law testing metrics throughput, path efficiency, average speed, number of timeouts, overshoot, stopping distance, and simultaneity.** ***Results:*** **The FMG-based classification system significantly outperformed the EMG-based classification system in both throughput (0.902±0.270) vs. (0.751±0.309), (ρ<0.001) and path efficiency (87.2±8.7) vs. (83.2±7.8), (ρ<0.001). Similarly, FMG-based regression significantly outperformed EMG-based regression in throughput (0.871±0.2) vs. (0.69±0.3), (ρ<0.001) and path efficiency (64.8±5.3) vs. (58.8±7.1), (ρ<0.001).** ***Conclusions:*** **The FMG-based schemes outperformed the EMG-based schemes regardless of which controller was used. This provides further evidence for FMG as a viable alternative to EMG based for human-machine interfaces.** ***Significance:*** **This work describes a comprehensive evaluation of the online usability of FMG and EMG-based control using both sequential classification and simultaneous regression control.**

Keywords— Force myography, electromyography, control, regression, classification, usability.

I. Introduction

The selection and suitability of control modality for upper limb prostheses varies depending on the number of control inputs and the complexity of the device under control. With the availability of multi-degree of freedom devices, pattern recognition-based myoelectric control systems, which are capable of intuitive control of multiple degrees of freedom [1][2][3], are now emerging as the clinical state-of-the-art.

Despite an overwhelming focus on EMG in the field of prosthetics, force myography (FMG) has also been proposed as a possible human-machine interface [4]–[7]. Instead of using the electrical activity generated during contractions, FMG uses force-sensing elements to measure the pressure distributions at the surface of the skin (or the skin-socket interface). These pressure profiles change with changing contractions, and FMG has been shown to yield higher classification accuracies than EMG based systems in offline studies [2][6]. Radmand *et al.* [6], for example, investigated a high-density FMG (hd-FMG) system and attained a 99.7% classification accuracy in an eight-class experiment.

It is often considered impractical to use more than eight EMG sensors due the cost, comfort, and complexity of the necessary instrumentation, but force sensors can be easily and inexpensively fabricated individually or in an array. Force sensing resistors (FSRs) have therefore been commonly used in studies involving FMG [8]–[12] as they are an inexpensive and versatile option for force sensing. Other resistive [13], pneumatic [14], and optical [15] based pressure sensors have also been evaluated. These systems range in sensor count from as few as eight sensors [16] to high-density grids of pressure sensitive elements [6] and even systems which concurrently collect EMG and FMG data [13].

Given its modest research focus compared to EMG, FMG-based pattern recognition has not readily been deployed clinically, although it may pose potential advantages over EMG. Because it is a naturally filtered signal, it requires less complex instrumentation and lower sampling rates than the more stochastic and higher bandwidth EMG signal. It has been shown to suffer from similar challenges as EMG, although similar mitigation approaches have proven beneficial. For instance, improved robustness to variations in limb position has been demonstrated when training using multiple positions or incorporating dynamic limb positions [6] [17].

In EMG studies, two different control modalities have been widely dominated the field of pattern recognition based control. The first are *classification*-based control schemes which have been studied using surface [18], intramuscular [19], and combined EMG signals [20], and partition the feature space into distinct classes. Alternatively, *regression*-based approaches continuously map the control input to position or velocity space in multiple degrees of freedom (DoF). Regression approaches

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have been extensively studied with EMG-based systems over the past decade using both offline metrics and real-time usability tests [15][21][22][23]. FMG-based regression control research has primarily focused on its ability to predict effort either in grip strength or in a single DoF such as wrist

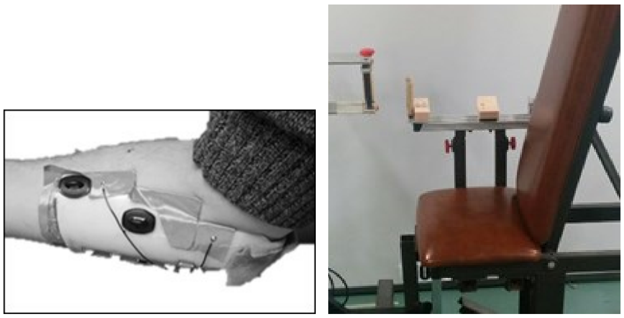

Fig. 1 – Photos of the cuff fitted to a forearm (left) and the armrest and wrist/hand restraint apparatus on the data collection chair (right).

pronation/supination [24], although some have predicted torques in three DoF for use in human-machine interfaces [25][26].

High classification accuracies, such as those attained in these prior studies, however, do not guarantee that FMG based devices will be robust in real-time use. In 2005, Lock *et al.* [27] found that EMG-based pattern recognition showed low correlation between offline classification accuracy and completion times in a virtual functional test. This is, in part, because usability involves multiple factors including feedback [28]–[30], understanding of the task itself [30][31], dynamics such as proportional control [32][33], and longer-term signal stability and repeatability [34][35]. Similarly, Ortiz-Catalan et al. suggested that offline accuracy may even be misleading [37].

Although the high offline classification accuracies demonstrated in previous FMG studies [6] [36]–[39] are promising, the real-time usability remains largely unexplored [26]. In this work, we therefor conduct a direct comparison between EMG- and FMG-based pattern recognition in a real-time target acquisitions task using both *classification* and *regression*-based controllers.

II. Methods

A. Participants

Twenty right-handed, able-bodied participants took part in this study (19 male, 1 female, mean age of 29.55 ± 9.77 years). All participants provided informed consent, as 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.

B. Experimental Protocol

Participants were seated comfortably with their elbow and wrist on an armrest, along with a wrist and hand restraint to limit any unintentional motion of the arm, as shown in Fig. 1.

All visual prompting and data collection was accomplished using a custom MATLAB™ graphical user interface which displayed visual targets and a cursor controlled by the participant on a screen placed in front of them as shown in Fig. 2 [42].

For both the EMG- and FMG-based systems, the *classification* and *regression* control methods were investigated as outlined below. For classification training, data were acquired for 5 classes of motion (wrist pronation/supination, hand open/close, and a no motion rest class). For each active class, four training repetitions of 4 seconds each were collected by having the user produce dynamic contractions with an intensity matched to a screen-based sinusoidal prompt that began at rest, increased to a peak contraction, then gradually decreased back to rest. This sinusoidal prompt serves as the target for both classification (direction) and regression (direction and amplitude) [43]. For regression, a unique regressor was trained for each degree of freedom by oscillating between antagonist motion pairs (wrist supination/pronation, and hand open/close). These regression training sessions lasted 8 seconds each to ensure equivalent amounts of training data between the two control schemes.

C. Fitts' Law Testing

Usability performance was evaluated for each of the four permutations of EMG/FMG and classification/regression, using a Fitts' law style target acquisition test, as previously described in [15][41]. Subjects used wrist rotation to rotate the cursor "dial" into a target zone, and hand open/close to move the entire cursor in the vertical direction, as shown in Fig. 2. Participants were asked to practice by acquiring 10 targets in the Fitts' law environment as an acclimatization period for each new control type. Once comfortable, participants completed the Fitts' Law target acquisition task, consisting of all combinations of three target widths (10, 15, and 25% of the screen size) and two target distances (50 and 100%), with a one-

Fig. 2 - An example of the Fitts' law-style virtual task for two degrees of freedom. Wrist pronation/supination were used to rotate the line cursor into the target arc, while hand open/closed was used to move the entire cursor vertically, into the square target

second target dwell time. A target was considered failed and timed out if not acquired within 10 seconds.

This entire process was completed four times for each of the four control schemes/systems tested, with a randomized order of appearance to mitigate any learning effects[1].

D. EMG Data Acquisition and Processing

EMG signals were collected using a cuff of 8 UNB smart electrodes [45]. Signals were analog notch filtered at 60 Hz, bandpass filtered between 20-450Hz using a 3rd order Butterworth filter, and sampled at 1000 Hz. The cuff was placed around the forearm of the subject, roughly one-third of the distance from the elbow to the wrist.

EMG features were extracted from 160ms windows overlapped by 16ms. The common set of time domain features proposed by Hudgins *et al.* [46] (mean absolute value, waveform length, zero crossings, slope sign changes) were extracted to represent the EMG data for classification. For the classification system, a support vector machine (SVM) classifier with a linear kernel was trained using the features extracted from all five classes, with proportional control derived by a class normalized mean of mean absolute values (MAV) approach [47]. For the regression case, a separate support vector regression (SVR) model was trained for each of the two DoFs. The same TD features were extracted as for the classification case, and the model was trained using the visual prompts as the training targets. In each case, the active data from the other DoF was re-labeled and included in the training as rest to reduce potential unintentional co-activation (e.g. periods of wrist pronation were included in the training of the hand open/close DoF but labeled as no-motion) [22][45].

E. FMG Data Acquisition and Processing

FMG signals were collected using a custom socket instrumented with three high-density force sensor boards provided by Smart Skin Technologies (Fredericton, New Brunswick). The grids of 16x24 sensor elements were similar to the those used in [6] but with higher resolution (due to availability). The sensors grids were adhered inside of a thermoset plastic cuff (roughly formed to fit an average forearm size, with some flexibility built in to accommodate a range of subjects) and anchored to the proximal forearm. The Smart Skin boards include their own internal sampling system and stream the full set of sensor values over Bluetooth at a rate of 15 Hz.

Although the FMG cuff contained 384 sensor elements in total, it has previously been shown [7] that so many sensors are unnecessary. As a result, only 6 contiguous circumferential rows (144 sensors in total) were used to avoid using distal rows or those compromised by socket fit [49]. Row selection was performed on a subject-by-subject basis (due to socket fit) using the R^2 correlation coefficient with the regression target as the selection criteria. Unlike EMG, which is stochastic and highly variable, FMG signals are naturally filtered by mechanical processes. As a result, the raw pressure sensor outputs can be used directly as features for FMG classification. As in the EMG case, an SVM classifier was trained using the 5 classes of motion for the FMG-based classification system. Similarly, the same approach as previously described with EMG was used to train the corresponding FMG-based regression system.

F. FMG-based Proportional Control

Real-time EMG classification-based control was achieved by pairing the classifier output with a commonly reported proportional control scheme (the average of the mean absolute values of all channels) [33]. For FMG, this traditional approach is insufficient, as the average FMG value does not increase monotonically with contraction intensity [49]. Although the mean amplitude of FMG channels produces a reasonable approximation for certain motions (those that primarily exhibit a uniform increase in pressure around the circumference of the arm) other motions exhibit an inverse relationship between contraction level and pressures recorded on certain channels (the muscle contracts inward).

In [49], a class-specific proportional control scheme was introduced based on a linear combination of FMG channel values. Similar class-specific approaches have also been reported to be beneficial for EMG [50]. This approach was implemented here by training class-specific SVR regression models with the classifier training data and the amplitude of the corresponding visual prompts as the regression targets. In this way, the proportional control output was computed during the Fitts' law style test using the class-specific regression model corresponding to the currently identified FMG class. Fig. 3 demonstrates an example of the performance of this approach.

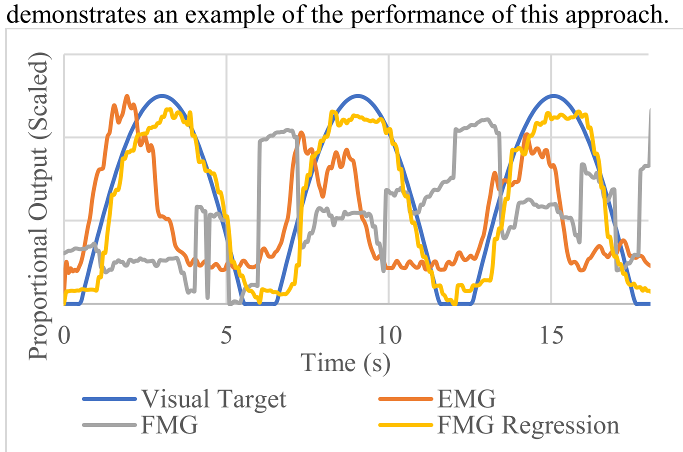

Fig. 3 - Proportional control outputs for EMG (MAV), FMG (MAV), and FMG (regression-based approach) vs. the target value for use as part of the classification control scheme

G. Performance Evaluation

Performance in the target acquisition test was evaluated using *throughput*, *path efficiency*, *number of timeouts*, *overshoot*, *stopping distance*, and *average speed*, as previously reported in [18], [43], [51], [52]. An additional metric –

[1] Although a random order was chosen for any given subject, the overall order of presentation was controlled. Specifically, each control system was teste first the same number of times, and it was ensured that the ordering of subsequent trials was similarly distributed. This avoided bias toward a particular control scheme due to learning effects.

simultaneity of movements – was also adopted, as defined below, for the regression-based control tasks.

Throughput (TP) is defined as the ratio of movement time to the index of difficulty (ID), where ID is proportional to the target width (W) and distance (D) to the target, as described in (2).

$$TP = \frac{ID}{MT} \tag{1}$$

$$ID = \log_2\left(\frac{D}{W} + 1\right) \tag{2}$$

Efficiency (EFF) for classification systems was defined as the ratio of the shortest Manhattan distance to the target (composed of horizontal (T_y) coordinate and vertical (T_y) coordinate components) divided by the horizontal (D_x) and vertical (D_y) distance traveled, as shown in (3):

$$EFF_C = \frac{|T_x| + |T_y|}{|D_x| + |D_y|} \tag{3}$$

For the regression systems, the Euclidian distance was used (to account for simultaneous activations of degrees of freedom), as shown in (4):

$$EFF_R = \frac{\sqrt{|T_x|^2 + |T_y|^2}}{\sqrt{|D_x|^2 + |D_y|^2}} \tag{4}$$

Average speed (AS) was computed as the average non-zero speed of the cursor over the trial. The *number of timeouts* (NT) was computed as the percentage of failed targets due to the 10-second timeout. *Overshoot* (OS) was computed as the average number of times a target was exited after initially being acquired. *Stopping Distance* (SD) was computed as the total distance traveled within the target during the one second dwell time. *Simultaneity* (SM) was calculated as the percentage of time that both DoF were active.

The results for each combination of sensor (EMG/FMG) control (classification/regression). Normality was evaluated based on skewness, ϒ, and kurtosis, Ꝁ, and data were considered normal for |ϒ|<1 and |Ꝁ|<2. Data were then tested using standard *t*-tests or the Wilcoxon-Mann-Whitney (*WMW*) test, accordingly. Results were considered significant for $p < 0.05$.

III. Results

A. Target Acquisition Trajectories

Fig. 4 and Fig. 5 show examples of the paths traveled by a representative inexperienced participant while acquiring the prompted targets over 4 trials for each of the control types. Note that the rotational element of the test, as shown in Fig. 2, is mapped here to the horizontal axis for easier visualization of the time series. The vertical axis denotes the same vertical motion (hand open/close) as in the Fitts' test. Also, note that each figure shows the various Fitts' targets superimposed over the four trials. Fig. 4a and Fig. 5a demonstrate the sequential behavior of classification-based control using EMG and FMG respectively, while Fig. 4b and Fig. 5b demonstrate the partial use of simultaneous activation with the regression-based controllers.

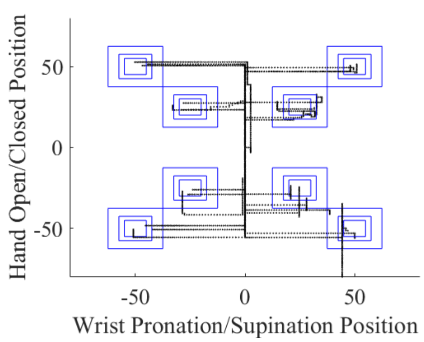

Fig. 4a - Example of paths travelled for four repetitions of a representative user for EMG classification-based control.

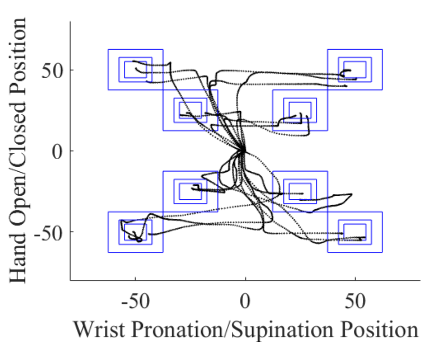

Fig. 4b - Example of paths travelled for four repetitions of a representative user for EMG regression-based control.

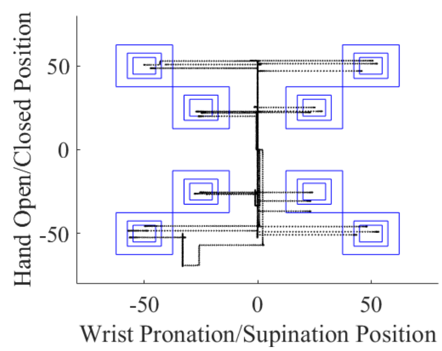

Fig. 5a - Example of paths travelled for four repetitions of a representative user for FMG classification-based control.

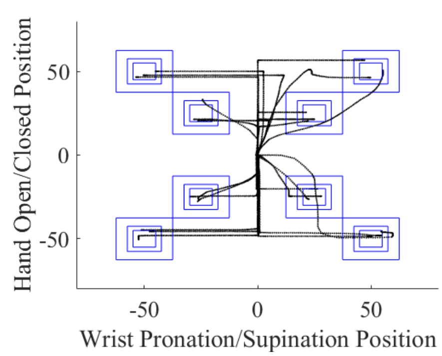

Fig. 5b - Example of paths travelled for four repetitions of a representative user for FMG regression-based control.

TABLE I

SUMMARY OF TARGET ACQUISITION TASK RESULTS FOR FMG AND EMG CLASSIFICATION AND REGRESSION-BASED CONTROL SCHEMES.

	CLASSIFICATION				**REGRESSION**			
	EMG	**FMG**	**TEST**	**P**	**EMG**	**FMG**	**TEST**	**P**
TP	0.75 ± 0.22	0.90 ± 0.27	*t*-test	<0.001	0.69 ± 0.20	0.87 ± 0.24	*t*-test	<0.001
EFF	83.2 ± 7.78	87.2± 8.71	*t*-test	=0.003	58.8 ± 7.13	64.8 ± 5.32	*t*-test	<0.001
NT	11.6 ± 14.4	6.00 ± 9.35	*WMW*	<0.001	8.23 ± 11.0	3.23 ± 6.53	*WMW*	<0.001
AS	54.9 ± 14.8	44.8 ± 11.6	*t*-test	<0.001	39.0 ± 10.1	31.6 ± 9.2	*t*-test	<0.001
OS	0.29 ± 0.45	0.34 ± 0.73	*WMW*	0.732	0.26 ± 0.40	0.15 ± 0.26	*WMW*	<0.001
SD	9.01 ± 3.88	9.18 ± 3.98	*t*-test	0.495	8.46 ± 3.38	8.20 ± 3.08	*t*-test	0.213
SM	N/A	N/A			22.5 ± 10.3	14.2 ± 10.6	*t*-test	<0.001

* Results shown as mean ± standard deviation; TP=throughput; EFF=efficiency (%); NT=trials that timed out (%); AS=average speed (% max); OS=overshoot (mean number of overshoots per trial); SD=stopping distance (bits), SM=simultaneity (% of time active).

** Columns *Test* and *P* denote the statistical test used and the corresponding p-value.

B. Performance Metrics

An independent samples t-test comparison of the *throughput* metric revealed that the FMG-based systems significantly outperformed the EMG-based systems for both classification and regression, as shown in Table I. For classification trials, the distributions of path efficiency for both EMG and FMG were highly skewed (-2.026 and -2.101 respectively; kurtosis was 6.749 and 7.264 respectively) due to several 100% efficient trials. After applying a logarithmic transform on the data, the skewness was reduced to -0.769 and -0.440, respectively. An independent samples t-test was then conducted to compare the efficiency between sensor types. The FMG-based system was found to have significantly higher path efficiencies than for classification-based control ($p = 0.003$).

For the regression trials, the path efficiency distribution for EMG was moderately skewed toward 100%, while the FMG results were approximately symmetric. Skewness values were -0.942 and -0.141 respectively; kurtosis was 3.296 and 0.176 respectively. An independent samples t-test indicated that FMG again had significantly higher path efficiencies than EMG ($p < 0.001$).

The average speed of the EMG-based system was significantly higher than FMG for both control types ($p<0.001$ in both cases). No significant difference was found between stopping distance of EMG and FMG-based systems for either of control types. An analysis of the use of simultaneous movements showed that subjects employed significantly more simultaneity with the FMG-based system than with the EMG system. After failing tests of normality, Wilcoxon–Mann–Whitney tests were conducted on the number of timeouts and overshoot. The FMG-based system was found to incur significantly fewer timeouts for both the classification and regression control schemes ($p<0.001$ in both cases). No significant difference was found between the overshoot for EMG and FMG-based systems for the classification trials. For the regression control trials, however, the FMG-based system yielded significantly less overshoot ($p<0.001$). ($p=0.732$).

As a secondary analysis, the performance of the regression and classification-based approaches were also compared within sensor type. In both the EMG and FMG-based sensor types, the classification control scheme yielded significantly higher throughputs ($p < 0.001$, and $p < 0.001$, respectively). This is consistent with recent results reported by Shehata et al [53], who showed that short-term classification performance was superior to that of regression in this form of a virtual target acquisition task.

C. User Preference

Participants were asked to subjectively rank the four combinations of sensor and control schemes based on their own perception of usability. Subjects were informed of this at the beginning of the experiment and reminded to maintain a mental ranking of the control types periodically throughout the procedure. Results were expressed as a simple ranking from best to worst perceived control (with a score of 1 for the best ranking to 4 for the worst) as shown in Table II. It should be noted that, although the order of presentation was randomized and not disclosed to subjects, it was not possible to truly blind them to which control scheme was being used. The sensor configurations necessitated the use of substantially different sockets and subjects could easily discriminate between sequential and simultaneous control.

TABLE II

USER SUBJECTIVE RANKING OF CONTROL SCHEMES; NUMBER OF TIMES RANKED IN EACH POSITION AND OVERALL MEAN RANK FOR EACH.

	RANKING				
Control	**1ST**	**2ND**	**3RD**	**4TH**	**MEAN**
EMG Class	1	2	9	8	3.2
EMG Reg	4	7	4	5	2.5
FMG Class	5	6	3	6	2.5
FMG Reg	10	5	4	1	1.8

* Class=Classification; Reg=Regression

IV. Discussion

Overall, the FMG-based systems consistently outperformed the EMG-based systems. This was true for both the classification and regression control schemes across nearly all metrics. This advantage was also reinforced by the subjective user ratings, which showed a preference for FMG.

No significant difference was found between the classification and regression approaches for either EMG ($p=0.059$) or FMG ($p=0.443$) despite a trend favoring the classification-based schemes (0.756 ± 0.222) versus (0.692 ± 0.200) and (0.902 ± 0.270) versus (0.871 ± 0.241) respectively. Conversely, subjects reported preferring the regression schemes for both the EMG and FMG-based systems.

It is interesting to note that average speed was significantly higher for EMG-based classification and regression than their FMG-based counterparts. This appeared to be due to a greater tendency to elicit lower control velocities for FMG to accomplish fine movements. This may also have been due to higher levels of EMG classification error at lower amplitudes [33], or due to differences in the fidelity of proportional control at these speeds. It was also found that subjects tended to instinctively contract more strongly in response to misclassifications when using both modalities. Given the higher incidence of error with the EMG controllers (as denoted by the lower efficiency and throughputs), this may have contributed to the higher average speeds.

The path efficiencies were found to be significantly higher for FMG for both control schemes. This suggests that participants were able to move more directly to the target with fewer extraneous movements. In many instances, participants exhibited sequential activations when using regression control with FMG, despite the availability of simultaneous control, as shown in some of the path traces in Fig. 5b. This is reinforced by the fact that subjects spent more time activating multiple degrees of freedom when using EMG than FMG. Despite this less efficient sequential behavior, participants still obtained higher efficiencies with FMG due to a higher overall accuracy. The lower simultaneity of the FMG-based regression may be a result of the regressor being finely tuned to individual classes (combined motions were not 'trained into' the model). Although it would increase training time, it is possible that incorporating combinations of DoFs during training would further improve performance and encourage the simultaneity, as has been shown with EMG [54].

It should be noted that this study included only able-bodied participants. Although this has been the case for most FMG studies thus far [4][36], some have included amputee participants [5][6] and supported the applicability of FMG for this population. In the EMG literature, similar relative trends have been found between able-bodied and amputee subjects (with a reduction in absolute accuracies) [57]. While the absolute performance of an FMG based system will likely be reduced when used by amputees due to lower muscle tone and volume [5], the amount of decrease remains to be determined.

A study involving amputees is ultimately required to determine the clinical utility of FMG. The focus of this work, however, was to conduct a carefully controlled study to compare the relative merits of FMG and EMG based system in a variety of conditions, including classification and regression controllers. This direct comparison in a real-time usability study is novel, and an essential step in the progression in the body of evidence for FMG-based control.

Although the use of FMG in a user-in-the-loop target acquisition task goes further toward meaningful usability assessment than previous work, the experimental protocol was still constrained. A natural and necessary progression will be to evaluate the performance of these systems in real usage scenarios (such as considering the effects of dynamic loading and external perturbations). Additional logic, such as rejection [58], will likely be required to accommodate the introduction of unknown pressure patterns.

V. Conclusion

FMG continues to show great promise as a control input for human-machine interfaces such as prosthetics. This investigation extended this affirmation from offline studies to a direct real-time performance comparison with an EMG-based system using the two most commonly used control schemes.

The FMG-based control consistently outperformed EMG-based control, whether using classification or regression, and was subjectively preferred by the users. Improvements in regressor design and/or training may further improve the degree of simultaneity of FMG.

Translation of FMG control to amputee populations will require careful consideration of the FMG sensor array design. It must be effectively customized to best capture muscle deformation while accommodating the wide variation in residual limb geometry, musculature, socket fit and skin conditions. Nevertheless, it has consistently demonstrated superiority in both offline and now online usability experiments, suggesting that it is worth continued investigation as an alternative or complement to EMG.

Ongoing work should seek to develop and evaluate methods of mitigating the effect of socket loading effects [59], either from dynamic motion of the limb, from the weight of objects being held, or through contact of the socket with exterior objects. This will necessitate the construction of custom and individually sized and fitted sockets for each subject, making it an ambitious but worthy pursuit. Additional use cases for other applications, such as human-computer interfaces, also hold promise and may be further investigated.

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