Pilot study on strategies in sensor placement for robust hand/wrist gesture classification based on movement related changes in forearm volume

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Abstract— **Force Myography (FMG) is novel method of tracking functional motor activity using volumetric changes associated with muscle function. With comparable accuracy and multiple advantages over traditional methods of functional motor activity tracking, FMG has made leaps and bounds in terms of applications in human-machine interfaces and healthcare devices. As a field that is rapidly gaining popularity in health innovation, the aim of this paper is to contribute to our understanding of the nature FMG methods and establish it as a robust and reliable technique. The main point of exploration for this study is the impact of sensor placement and spatial coverage on FMG methods. Five participants were invited to perform a series of isolated wrist motions and hand gestures while wearing custom built FMG devices. Linear Discriminant Analysis (LDA) machine learning models were developed using 80% of the data for training and 20% for testing. Overall, the accuracy of the LDA models ranged from 75% to 100% across all subjects and dimensions of FMG data. The model accuracy improved when increasing the spatial coverage from 1 FMG band to 2, but it did not increase further with additions. The results also showed that the improved accuracy offered by a large spatial coverage of FMG data can be approximated by lower spatial coverage if sensors were place in an optimal location. This location was indicated to be midway between the wrist and the collective muscle bellies of intrinsic forearm muscles. The knowledge generated from this work aims serve as a guide towards the development of portable FMG based technology for widespread deployment in the general population. The hope is that the long-term benefits of continued FMG research will address issues in healthcare associated with disparities in access to medical technologies.**

I. INTRODUCTION

Force Myography (FMG), also known as Residual Kinetic Imaging (RKI) [1] or Muscle Pressure Mapping (MPM) [2], is a technique that is based on the volumetric changes in muscle that occur with contraction and relaxation [3-4]. By tracking the volumetric patterns associated with the contraction of groups of muscles, we are able to develop predictive machine learning models of gross motor function. The applications of FMG range from being a user interface for the control of external technology [1-5], like prosthetic devices, as well as the monitoring and tracking of movements within rehabilitative contexts [6-7].

Although other sensor modalities, such as Electromyography (EMG), have traditionally been used to track muscle activity and motor function, FMG as measured by tactile sensors provides several advantages. Advantages of FMG are that: (1) it does not require precise sensor placement, (2) it does not require extensive skin preparation, (3) it does not require the same level of signal processing required in EMG datasets, and lastly (4) it is a more affordable alternative to other muscle activity tracking methods [8]. These advantages allow FMG techniques to address issues such lack of professional training, poor medical infrastructure, and lack of resources that aggravate disparities in access to medical technology. With comparable accuracy to surface EMG and ultrasound imaging, FMG is an ideal candidate for future development of low-cost & novel solutions for movement related issues, injury prevention strategies in industrial settings, long-term healthcare monitoring, and implementation within assistive/rehabilitative designs [9].

As a developing field of study, myo-pneumatic (M-P) sensors [1] and optical fiber sensors [8,10] are examples of sensor modalities used in FMG research, with force sensitive resistors (FSRs) being the most common due to their ease of incorporation into prototype designs and simple circuitry [3-7,11-12]. The implementation of FSRs in FMG related research ranges from single vector designs to extensive arrays with larger spatial coverage, as well as a variety of resolutions and sensitivities to provide pressure maps that are indicative of force production and motor activity [7].

With respect to upper extremity motor activity, FMG using FSRs already has successfully been used to classify hand gestures and grasp types significant to Activities of Daily Living (ADLs) [4-5,8], classify fine finger movements [1,13], regress force production [3], and to control a prosthetic device [7]. Despite these recent advances, however, the nature of FMG as a measurement technique still requires further study to establish FMG as a robust and reliable method in upper extremity motor tracking research.

Thus, the objective of this paper is to contribute to the growing understanding of the nature of FMG measurements by considering the impact of spatial coverage and sensor placement. To accomplish this, participants were invited to complete a variety of hand gestures and wrist motions while wearing a custom designed portable FMG device. We hypothesize that FMG sensor placement and overall spatial coverage, with the respect to the length of the forearm, will significantly impact the accuracy and predictability of machine learning models of upper extremity movement.

This paper is organized as follows: section II outlines the materials used, proposed experimental protocol, and analysis; section III provides an overview of experimental results, which are then discussed in section IV. Concluding remarks are presented in section V.

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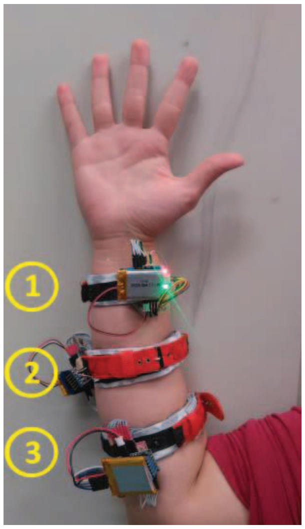

Figure 2 Placement of custom FMG bands on participant's forearm. (1) approximately 2.25 cm proximal to the wrist, identified by the surface landmarks of the radial and ulnar styloid processes (2) midway between the band at position 1 and the point on the forearm with the widest circumference, and (3) the point on the forearm with the widest circumference.

II. Materials and Methods

A. Force Myography

A custom FMG band was designed in house for this protocol. The band utilizes 16 Force Sensitive Resistors (Model 400, Interlink Technologies) in series, and spaced 2 cm apart. Each Force Sensitive Resistor (FSR) is implemented in a voltage divider circuit with a 4.7 kΩ resistor and V_{DD} of 3.7 V. An ATMega328 microprocessor was used to facilitate data collection and transmission. The FSRs were sampled at approximately 10 Hz, and raw values were timestamped and transmitted to an on-site computer via serial connection and saved onto a .txt file for offline processing.

Towards understanding the role of sensor placement and spatial coverage of FMG methods, participants donned three bands simultaneously on the forearm while completing a predefined protocol. The FMG bands were placed at the following landmarks on the forearm: (1) approximately 2.25 cm proximal to the wrist, identified by the surface landmarks of the radial and ulnar styloid processes (2) midway between the band at position 1 and the point on the forearm with the widest circumference, and (3) the point on the forearm with the widest circumference. While the widest part of the forearm is characteristically associated with the muscle bellies of intrinsic forearms musculature, for the purposes of results reporting, this landmark be referred to as 'the muscle belly of the forearm'. The placement of these three bands used for all participant are shown above in Figure 1.

B. Participant Protocol

All participants performed a set of 8 movements, 4 hand gestures and 4 wrist gestures. The four hand gestures used in this protocol were: relax, open, fist, and point. The four wrist motions used were: flexion, extension, pronation, and supination. The experiment facilitator demonstrated each gesture prior to administering the protocol. Figure 2 below provides a visual overview of the gestures used in this protocol. While participants completed the protocol, they were asked to maintain an elbow angle of 90 degrees and a shoulder angle of 0 degrees. Gestures were held 7 seconds each, with 5 repetitions for each gesture. All subjects provided informed and written consent, and the test procedure was approved by the Simon Fraser University Office of Research Ethics

C. Analysis

Analysis was performed offline in MATLAB v2015b. Raw FMG data was normalized and used to classify gestures using Linear Discriminant Analysis (LDA) machine learning. Training and testing for each individual subject was performed using 4 and 1 repetitions respectively. LDA classification was repeated for all possible combinations of FMG measurements from the 3 landmarks shown in Figure 1. All tests of significance were performed with a significance

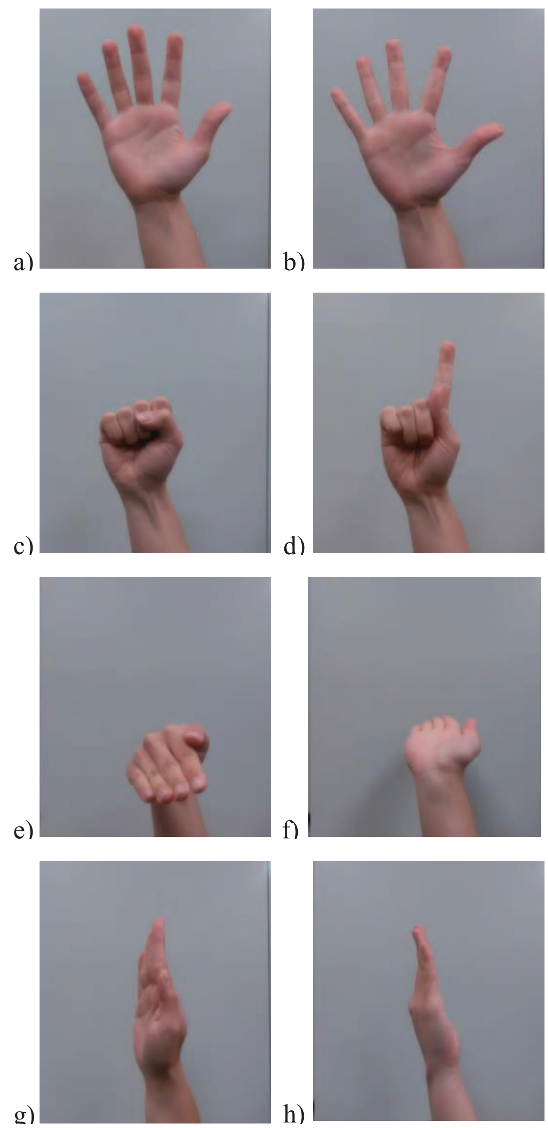

Figure 1 Going from left to right the gestures were a) relax, b) open, c) close, d) point, e) wrist flexion, f) wrist extension, g) wrist pronation, and h) wrist supination. Gestures a-d) were performed with a neutral wrist

TABLE 1 SUBJECT DEMOGRAPHICS

Subject	Forearm length (cm)	Circumference (cm)		
		Position 1	*Position 2*	*Position 3*
1	26	15.5	19	25.5
2	26	17	21	28
3	26	16.5	23	26
4	25	14	16.5	22
5	22	18	21	26
Average (mean ± st.dev)	25±1.73	16.2±1.52	20.10±2.46	25.50±2.18

**Position (1) is approximately 2.25 cm proximal to the wrist, identified by the radial and ulnar styloid process surface markers (2) is midway between the band at position 1 and the point on the forearm with the widest circumference, and (3) is at the point with the widest circumference

threshold of 0.05.

III. RESULTS

There were 5 participants (24.60 ± 2.07 years old) with no self-identified musculoskeletal injuries or limitations in range of motion. Two anthropometric measurements of the forearm were also taken. The first measurement taken was of the forearm length, which was taken from the ulnar styloid process (bony prominence of the wrist on the side of the pinky) to the olecranon (the bony prominence of the elbow). The second measurement taken was of the circumference of the forearm at each band landmarks shown in Figure 1. The average forearm length was 25 ± 1.73 cm for all five participants with circumferences of 16.2 ± 1.52 cm, 20.10 ± 2.46 cm, and 25.50 ± 2.18 cm at landmarks 1, 2, and 3 respectively. Subject specific anthropometric data are shown in Table 1 above.

Overall, the R^2 of LDA results were generally high ($\geq$ 0.75) across all subjects for all combinations of FMG sensor placement and spatial coverage. Results of subject specific LDA classification and group performance are provided in Table 2 and generalized in Figure 3.

When considering FMG band placements at only 1 landmark on the forearm, the results demonstrated improved accuracy and consistency when placed in the middle of the forearm with (mean ± standard deviation) 0.952 ± 0.172 accuracy, vs 0.907 ± 0.036 and 0.76 ± 0.117 when FMG was used at the wrist and forearm muscle belly respectively. FMG measurements solely at the muscle belly demonstrated the lowest and least consistent classification accuracy, as indicated by lower R^2 value and higher standard deviation in mean R^2 respectively.

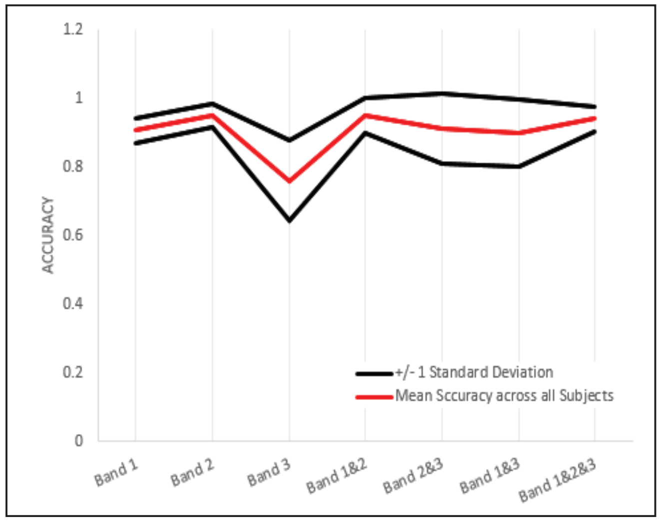

Figure 3 Average LDA classification accuracy across all subjects

Increasing the spatial coverage of FMG measurements from an FMG band at a single landmark to combinations of FMG bands from multiple landmarks resulted in similar classification accuracy and consistency for all subjects. However, there do not appear to be additional improvements in LDA R^2 values beyond combined FMG measurements from 2 landmarks, as LDA model R^2 values for 2 and 3 landmarks performed similarly.

Upon visual inspection of average performance, overall peak accuracy (mean ± standard deviation: 0.95 ± 0.036) was achieved using a combination of FMG measurements from the wrist and the middle of the forearm, as well as only from the middle of the forearm. These landmarks are associated with higher bulk of tendinous tissue in the sensor area(s). On the other hand, peak consistency (standard deviation less than 0.05) occurred by using a combination of FMG measurements that included the wrist or the middle of the forearm.

TABLE 2 R^2 FOR LINEAR DISCRIMINANT ANALYSIS (LDA) MODELS FOR ALL SUBJECTS

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	All Subjects
Band 1	0.998 ± 0.003	0.884 ± 0.04	0.94 ± 0.05	0.94 + 0.065	0.767 ± 0.102	0.907 ± 0.036
Band 2	0.991 ± 0.019	0.96 ± 0.045	0.999 ± 0.0014	0.993 + 0.01	0.79 ± 0.09	0.95 ± 0.036
Band 3	0.56 ± 0.35	0.858 ± 0.11	0.93 ± 0.07	0.90 + 0.116	0.557 ± 0.076	0.76 ± 0.117
Bands 1 and 2	1.00 ± 0.00	0.967 ± 0.048	1.00 ± 0.00	1.00 ± 0.00	0.796 ± 0.116	0.95 ± 0.051
Bands 2 and 3	0.788 ± 0.243	0.98 ± 0.04	1.00 ± 0.00	1.00 ± 0.00	0.79 ± 0.098	0.91 ± 0.102
Bands 1 and 3	0.81 ± 0.21	0.976 ± 0.036	0.976 ± 0.045	1.00 ± 0.00	0.73 ± 0.196	0.899 ± 0.098
Bands 1, 2, and 3	0.944 ± 0.077	0.985 ± 0.033	1.00 ± 0.00	1.00 ± 0.00	0.792 ± 0.069	0.94 ± 0.037

IV. Discussion

The results of this study demonstrates some important features of FMG methods that would prove significant to further research and novel device development. One important feature suggested by the results of this study is that increased spatial coverage along the length of the limb improves classification accuracy of an FMG based gesture model. This is evident by the increased R^2 value of LDA models based on FMG measurements from two or more landmarks. However, the similarity in performance of using FMG measurements from 2 vs 3 landmarks suggests further increases in FMG spatial coverage would not correlate to further improvements in LDA performance.

In further considering LDA models based on FMG measurement from 2 landmarks, it appears that the spatial separation of the FMG sensors also plays a role. In relation to the landmarks proposed in Figure 1, the underlying forearm anatomy becomes mores tendinous in nature moving from the forearm muscle belly to the wrist. Thus, high accuracy of LDA models that used landmarks 1 and 2 suggest FMG sensor placement more closely associated with tendinous tissue yields improved accuracy. However, the increased consistency of LDA results using landmarks that were not only farther away from each other, but also had greater differences in underlying tissue structure, should also be considered. This would be particularly significant for wider scale studies, where inter- and intra-subject consistency in health related research is key.

Lastly, although the data suggests that increased spatial coverage (as indicated by multiple landmarks in FMG measurements) increases classification accuracy, this improved performance can be approximated using a single landmark. The ideal landmark for this is shown to be midway between the forearm muscle belly and the wrist, which is also corresponds to the area of transition in underlying forearm structures from muscle bulk to tendinous tissue. This would have positive impacts on the design of portable consumer FMG technology, as it allows for smaller streamlined designs with fewer sensors and comparable performance. However, an additional implication is that accuracy and consistency would be sacrificed in consumer technology, as most devices for the forearm are designed to be worn at the wrist.

In light of the positive results of this study, there are some limitations in the protocol that should be addressed. One of the limitations is the sample size and the set of gestures used in this study, which would be expanded in the future to allow for more concrete conclusion.

As this protocol only considered gestures in isolation, a consideration for compound gestures would ring more true to activities of daily living. An example would be removing a jar lid, which would incorporate both the power grasp of holding onto the lid, and radial/ulnar deviation of the wrist to twist the lid off.

Consideration of the impact of elbow range of motion is also significant as this protocol was limited to 90 degrees' of elbow flexion. General movements of the upper arm are a result of compound movements of finger, wrist, elbow, and hand joints. This would prove problematic in the recognition forearm pronation/supination, which would be indistinguishable from shoulder internal/external rotation at full elbow extension. This would impact activity tracking during protocols directed towards rehabilitation of targeted movements of specific joints.

Lastly, a promising field of research would include sensor fusion of FMG data with other sensors types, such as inertial sensors. This would provide extensive opportunities for comprehensive motion and activity tracking, and would lead to improved real-time control of external devices.

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References

[1] S. L. Philips and W. Craelius, "Residual kinetic imaging: a versatile interface for prosthetic control," *Robotica,* vol. 23, no. 03, pp. 277-282, 2005.

[2] A. Radman, E. Scheme and K. Englehard, "High resolution muscle pressure mapping for upper limb prosthetic control," 2014.

[3] M. B. Wininger, N.-H. Kim and C. William, "Pressure signature of forearm as predictor of grip force," *Journal of rehabilitation Research & Development ,* vol. 45, no. 6, pp. 883-892, 2008.

[4] C. Erina, C. Richard, L. K. Merhi, X. Zhen, P. Brittany and M. Carlo, "Force Myography to Control Robotic Upper Extremity Prostheses: A Feasibility Study," *Frontiers in Bioengineering and Biotechnology,* vol. 4, no. 18, 2016.

[5] E. Fujiwara, Y. T. Wu, M. F. M. Santos, E. A. Schenkel and C. K. Suzuki, "Identification of Hand Postures by Force Myography Using an Optical Fiber Specklegram Sensor," in *24th International Conference on Optical Fibre Sensors*, Curitiba, 2015.

[6] Y. Honda, S. Weber and T. C. Lueth, "Intelligent recognition system for hand gestures," in *3rd International IEEE EMBS Conference on Neural Engineering*, Kohala, 2007.

[7] P. Heo, G. Min Gu, S.-j. Lee, K. Rhee and J. Kim, "Current Hand Exoskeleton Technologies for Rehabilitation and Assistive Engineering," *International Journal of Precision Engineering and Manufacturing,* vol. 13, no. 5, pp. 807-824, 2015.

[8] Z. G. Xiao and C. Menon, "Towards the Development of a Wearable Feedback System for Monitoring the Activities of the Upper-extremities," *Journal of NeuroEngineering and Rehabilitation,* vol. 11, no. 2, 2014.

[9] M. Kuttuva, G. Burdea, J. Flint and W. Craelius, "Manipulation Practice for Upper-Limb Amputees Using Virtual Reality," *PRESENCE,* vol. 14, no. 2, pp. 175-182, 2005.

[10] O. Amft, H. Junker, P. Lukowicz, G. Troster and C. Schuster, "Sensing Muscle Activities with Body-Worn Sensors," in *International Workshop on Wearable and Implantable Body Sensor Networks*, Washington, 2006.

[11] 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," in *2015 IEEE International Conference on Mechatronics (ICM)*, Nagoya, 2015.

[12] V. Ravindra and C. Castellini, "A Comparative Analysis of Three Non-invasive Human-machine Interfaces for the Disabled," *Frontiers in Neurorobot,* vol. 8, no. 24, 2014.

[13] N. Li, D. Yang, L. Jiang, H. Liu and H. Cai, "Combined Use of FSR Sensor Array and SVM Classifier for Finger Motion Recognition Based on Pressure Distribution Map," *Journal of Bionic Engineering,* vol. 9, no. 1, pp. 39-47, 2012.

[14] P. Bonato, "Advances in wearable technology and applications in physical medicine and rehabilitation," *Journal of NeuroEngineering and Rehabilitation,* vol. 2, no. 2, 2005.