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# FSR based Force Myography (FMG) Stability Throughout Non-Stationary Upper Extremity Tasks

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***Abstract*—Force Myography (FMG) is a method of tracking movement and functional activity that is based on the volumetric changes that occur in a limb during muscle contraction. There are several advantages of FMG over other myographic modalities that support its implementation in rehabilitative and assistive technology to track upper extremity movement during activities of daily living. The aim of the current work is to explore the stability of FMG sensors during non-static upper extremity activities. Twenty-one participants with varying age and gender were recruited to perform a set of tasks while wearing a custom FMG band. The participants were required to move between two extremes of range of motion (wrist flexion/extension and forearm pronation/supination) or between two extremes of grasp force (squeeze and relax). FMG presented low variability (<6%) and demonstrated little to no drift with ongoing task duration (Spearman's |R| < 0.3). FMG variability did not present any relationship to differences in anthropometry or grip strength (Spearman's |R| < 0.3), suggesting that FMG wearers will present a stable FMG signal despite differing musculoskeletal characteristics. Finally, variability in FMG presented no significant relationship between user variables and the testing accuracies of machine learning models trained on FMG data. The results of this study demonstrate the stability of FMG signals during non-stationary tasks and support the potential of implementing FMG into user-machine interface technology.**

***Keywords—Activities of daily living; age-related rehabilitation; assistive technology; biomedical devices; human factors; independent living; prosthetic control; sensors/sensor application; force myography***

## I. INTRODUCTION

Force myography is a technique of tracking movement and motor activity, and is relatively new when compared to other myographic methods. As such, there is a lot of opportunity to better understand its strengths and limitations as a user interface technology. Myography, generally, refers to a method of data collection that characterizes the force produced by a muscle during contraction. The method is particularly useful for tracking patterns of movement and activity using regression and classification techniques. The applications for myography ranges from activity monitoring, rehabilitative devices/systems, assistive devices/systems, prosthetic limbs, gesture recognition and classification. Myography exists in multiple forms: Mechanomyography, Ultrasound Myography, Optical Myography, Electromyography, and Force Myography. Each of these forms operates on different principles.

Mechanomyography (MMG), is based on the resonant oscillations of muscle tissue during contraction [1]. It has successfully been used to monitor muscle fatigue [2], control prosthesis [3], track balance [4], and classify hand gestures [5]. Unfortunately, MMG usage typically requires a significant amount of signal processing [6] and there aren't any successful attempts to fashion MMG into a wearable and portable device. This is possibly due to its sensitivity to muscle artifacts [1].

Ultrasound Myography (UMG) uses Doppler ultrasound to measure muscle movement velocity, which is directly related to muscle force production [7]. The main uses for UMG have been for diagnostic and therapeutic purposes [7], with a few applications in the control of peripheral devices [8]. Unfortunately, acoustics fields created by ultrasound have been known to give rise to heating [7] which can lead to tissue damage, most ultrasound technologies are too expensive [8], and the ultrasound probe is too large for practical use [8].

Optical Myography (OMG) relies on optically tracking the skin undulations that occur with gesture formation [9], which is distinct from MMG which tracks vibrations at the skin's surface. However, all OMG studies thus far have been limited to having the arm in fixed positions [9], and have yet to address the nature of occlusion and visual noise that typically plague vision-based movement tracking systems.

Electromyography (EMG) measures the electrical activity that occurs with muscle depolarization during activation, and can be achieved with either intramuscular electrodes or surface electrodes [10]. EMG is distinguished by its far and wide reaching applications, and is the preferred implementation for rehabilitation and human interface purposes. Applications of EMG [11] range between ergonomics, exercise physiology, rehabilitation medicine, biofeedback, and the control of exoskeletons and prostheses. There are several challenges associated to using surface electromyography (EMG), including: inherent noise in the electrode, movement artifacts, electromagnetic noise, cross talk, artifacts from heart depolarizations, skin formation, blood flow velocity, skin temperature, tissue structure (composition of muscle, fat, etc.), and the measuring site [12]. Although many of these challenges can be addressed through machine learning and data preprocessing [12], constricted computing resources may be a limiting factor for small wearable implementations.

Finally, Force Myography is based on the increase in limb cross sectional area that occurs with muscle contraction. The predictive power of FMG comes from tracking the pressure changes along the surface of the skin for gesture recognition and the control of devices. The inclusion of FMG has gained momentum in innovative device designs typically dominated by EMG [13], and it demonstrates several advantages over previously motioned myographic methods. These include that it: 1) is robust to external electrical interference and sweating [14]; 2) does not require precise sensor placement or extensive skin preparation [15]; 3) does not require the same level of signal processing required in EMG datasets [16]; 4) can be a cost effective method of tactile sensing, with off-the-shelf discrete FSRs sensors costing less than $10 [17]; and 5) FMG signals are more stable over time during static gestures [18]. In addition, the nature of the sensors used in FMG acquisition is not associated with increasing tissue heat, as ultrasound is.

Most FMG research has focused on implementations with Force Sensitive Resistors (FSRs), which present variable resistance depending on the amount of force applied [22], [23]. FMG has already been fashioned into portable devices and has mainly been used on the upper extremity. For FMG collected on the arm, the underlying tissue is composed of muscle tissue, bone, connective tissue, adipose tissue, and skin - each which their own distributions, mechanical properties, and age-related changes. Despite the variability in underlying tissue within a population, FMG has been successfully used in areas of rehabilitation [19], device/prosthetic control [15], [18], gait analysis [20], and grip strength analysis [21]. However, given these areas of promise, FMG research would benefit from further characterization of the strengths and limitations of FMG signals during functional tasks.

One area that warrants further development, and is the focus of this current work, is the characteristics of FMG signal stability during non-stationary activity. To date, most of the work with FMG has involved static gesture and hand/wrist orientations classification. However, the study of FMG in non-static scenarios presents an opportunity to expand the application of FMG with increased confidence in its signal quality.

This manuscript is organized as follows: Section II outlines the methods of the study, including participant recruitment, instrumentation, experimental protocol, and data processing/analysis. Section III provides an overview of the descriptive statistics of the recruitment pool, as well as the results for the experimental protocol. Finally, avenues for future study are presented in Section IV, with concluding remarks in Sections V.

## II. Methods and Materials

### *A. Participants*

Participants were recruited from the students, faculty, and staff of Simon Fraser University. Inclusion criteria for participation required that participants can follow the instructions of the experimental protocol and perform the required gestures/tasks to completion. Exclusion criteria were limited to self-identified neurological or musculoskeletal barriers to functional movements of the upper extremities. All participants provided informed and written consent. Save for muscle fatigue, there was little to no risk to participants.

### *B. Instrumentation*

The primary instrumentation for this work is a custom designed FMG sensing device, lined with 16 polymer-thick-film FSRs (25.5 $mm^2$ active areas) in a staggered design. Smaller FSRs (Interlink Technologies, model: 400) were used to allow for placing the FSRs in closer proximity to each other, without overlapping the active areas. They were also used to maximize the number of discrete FSRs in contact with the skin at one time. The FSRs were backed with Flex foam and fastened to a flexible and non-elastic backing used for the interior of the band. As the data sheet for FSRs recommends more rigid backing in implementation [22], the cellulose acetate backing was used to facilitate better contact between the FSR's and the skin while allowing the band to conform to the shape of the wrist. The FMG band is shown in Fig. 1.

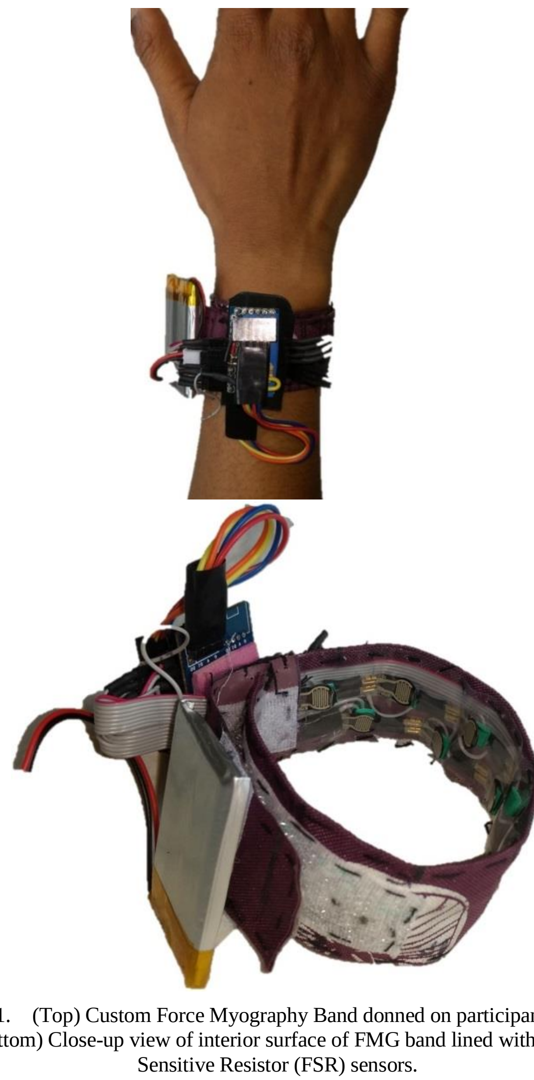

Fig. 1. (Top) Custom Force Myography Band donned on participants arm. (Bottom) Close-up view of interior surface of FMG band lined with Force Sensitive Resistor (FSR) sensors.

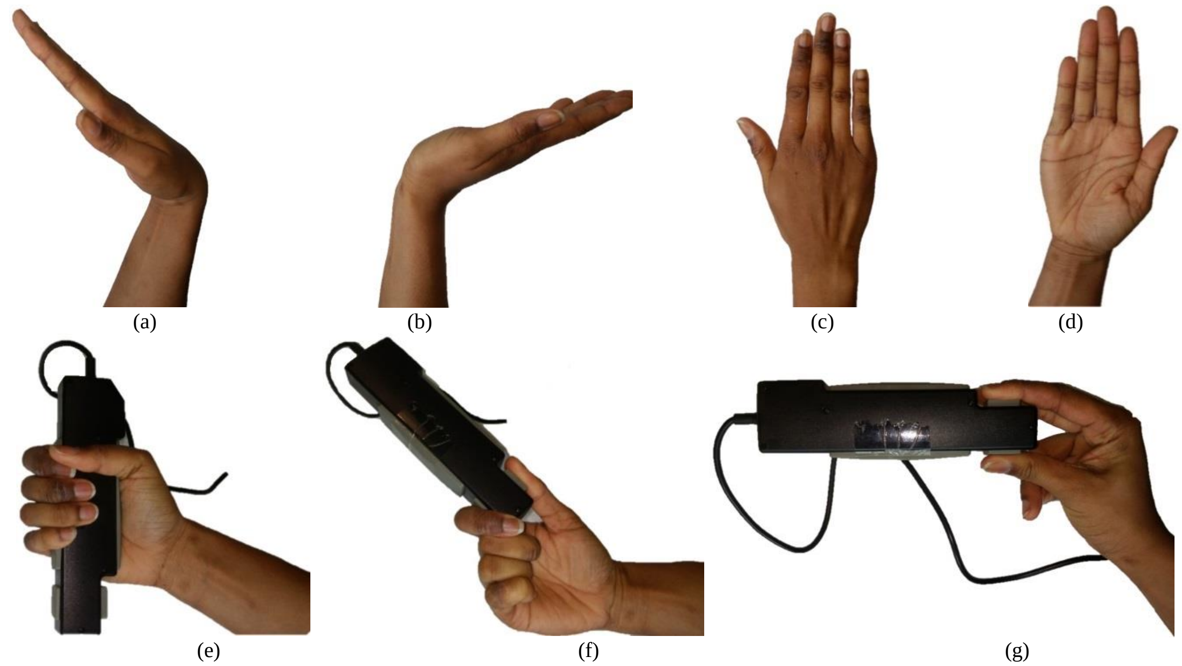


Fig. 2. Experimental Protocol. Note. Motions Shown are (a) Wrist Flexion, (b) Wrist Extension, (c) Forearm Pronation, (d) Forearm Supination, (e) Cylindrical Grip, (f) Key Grip, (g) Tripod Grip. The object held in tasks e-g is the Vernier Hand Dynamometer (Model HD-BTA).

FSRs were implemented in a series with a 4.6 kΩ resistor and supplied with 3.7 V. An ATMega328 microprocessor was used to facilitate data collection and transmission. Each FSR was sampled at approximately 10 Hz, with raw analog values converted to a digital signal ranging from 0 to 1023 (0.00361 V/bit). Digital values were time stamped and transmitted to an on-site computer via serial connection and saved to a .txt file for offline processing in MATLAB 2016b.

In addition to FMG at the wrist, the following features and their associated measurement methods were also included: hand grip strength (Vernier Software & Technology, model: HD-BTA), forearm and wrist circumference, skin contact pressure (Force Sensitive Resistor, Model: 400, Interlink Technologies), angle of wrist flexion/extension (TT Electronics/BI Rotary Potentiometer, model: P160), and angle of forearm pronation/supination (SparkFun 9DoF IMU Breakout - LSM9DS1).

## C. Experimental Protocol

Measurements and testing were performed while participants sat at a chair of standard height and depth. Instructions were given as images via a custom LabVIEW visual interface. All tasks were performed with a neutral shoulder and elbow flexed to approximately 90°. To explore the stability of FSR based FMG in repetitive no-static conditions, each participant was instructed to perform five tasks which consisted of either moving between two extremes of range-of-motion or producing a grip with minimal to maximal effort. These five tasks were: 1) wrist flexion and extension; 2) forearm pronation and supination; 3) cylindrical grip squeeze and relax; 4) lateral pinch squeeze and relax; and 5) tripod squeeze and relax. Participants performed two repetitions of each dynamic motion for 60 seconds. These tasks are visualized in Fig. 2.

## D. Data Processing and Analysis

The dependent variable considered for this protocol is the variability of FMG recordings obtained during non-static repetitive activity. An approximate linearization was applied to FMG by taking the inverse of each value. The FMG signal was then sorted either by amount flexion/extension/pronation/ supination or the amount of grip force exerted at that instantaneous FMG sample. Finally, the linearized and sorted signal was filtered using a low-pass Butterworth filter, as shown in Fig. 3. FMG variability, as discussed in this work, was described as the root mean square (RMS) residual between the raw signal and filtered signal, as shown below in (1):

$$residual = \sqrt{\sum_i^N \left(FMG_{raw} - FMG_{filtered}\right)^2} \quad (1)$$

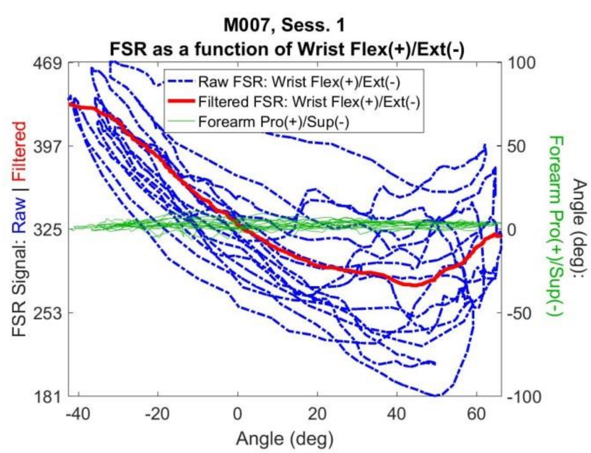


Fig. 3. Example of variability in a sensor through repetitive movements. Note: Shown above are the raw FSR readings (blue), the filtered signal (red). The readings pertain to wrist flexion/extension, so forearm pronation/supination is shown (green).

Sources of variability and the significance of variability on machine learning with FMG were also considered. Impact of FMG variability on machine learning was illustrated using: Artificial Neural Network (ANN), Extreme Machine Learning (ELM), Linear Discriminant Analysis (LDA), and Support Vector Machine (SVM). Student's t-Test, ANOVA, and Spearman's correlation coefficient (R), Coefficient of Determination ($R^2$) were used to evaluate the interaction between variables of interest. Significance tests were based on a significance level of ($p < 0.1$).

## III. Results and Discussion

There were 21 participants in this study, who were grouped according to age and gender to illustrate any age or gender associated with differences in FMG variability. Table 1 provides a general overview of the descriptive statistics of the recruitment pool.

All participants were right hand dominant – except for 3 left-hand dominant participants (2 senior females, and 1 non-senior male). The measurements for weight, height, BMI, wrist circumference, forearm circumference, forearm length, wrist flexion/extension, and forearm pronation/supination fall within the bounds set by age and gender matched norms [24]-[28]. Grip strength demonstrated similar age/gender matched patterns as Canadian National norms [29]; however, grips strengths measured were significantly lower. This is attributed to differences in instruments. Canadian tests utilized a deformable hand dynamometer, which would allow for optimal hang/digit configuration, whereas the hand dynamometer used in this work was non-deformable. For wrist flexion/extension and forearm pronation/supination, the active range of motion (aROM) during testing was at least 60% of the full aROM measured offline. Likewise, grip strength measurements were at least 60% of the maximum voluntary grip strength.

TABLE I. Descriptive Statistics

| | | **Non-senior** | | **Seniors** | |
|---|---|---|---|---|---|
| | ***Units*** | ***Female*** | ***Male*** | ***Female*** | ***Male*** |
| N | -- | 6 | 9 | 4 | 2 |
| (A) Age | years | 26.25 (2.44) | 27.11 (3.55) | 74.75 (5.44) | 64.50 (4.95) |
| (W) Weight | kg | 65.40 (14.71) | 87.11 (9.25) | 74.50 (15.51) | 82.41 (3.41) |
| (H) Height | m | 1.61 (0.04) | 1.83 (0.08) | 1.59 (0.07) | 1.65 (0.07) |
| (WC) Wrist Circumference | cm | 15.92 (1.88) | 17.72 (0.97) | 16.88 (1.80) | 19.25 (0.35) |
| (FC) Forearm Circumference | cm | 24.33 (2.82) | 27.50 (3.82) | 25.00 (1.78) | 27.25 (0.35) |
| (MGS) Max Grip Strength | kg | 24.79 (5.74) | 26.12 (5.50) | 13.18 (5.78) | 17.89 (1.83) |
| Wrist Flexion | degree | 75.83 (11.69) | 64.89 (15.03) | 58.25 (12.61) | 70.00 (7.07) |
| Wrist Extension | degree | 70.83 (9.70) | 66.89 (8.22) | 58.50 (7.51) | 56.00 (15.56) |
| Forearm Pronation | degree | 91.17 (13.79) | 88.44 (5.15) | 93.00 (5.60) | 86.00 (1.41) |
| Forearm Supination | degree | 98.33 (6.89) | 98.22 (13.20) | 93.50 (6.03) | 95.50 (10.61) |

*Values are presented as μ ($\sigma^2$), where μ is the mean and $\sigma^2$ is the standard deviation*

Approximately 95% of residuals calculated only represent between 2.85% to 6.47% of the range of FMG readings. Greater detail of the distribution of residuals for each of the tasks is shown in Fig. 4.

### *A. Sources of Variability*

This variability could come from several sources. One source is the relaxation of skin around the FSR sensors after the initial compression during band donning. However, there was low (|R|<0.3) to no correlation between the magnitude or direction of residuals and the ongoing duration of the trials. These results are summarized in Fig. 5. A second source of variation in angle of other joints was considered. However, as tabulated in Table 2, the wrist and forearm angle were stable through dynamic tasks, with standard deviations ranging from 0 and 2 degrees. A third source of variability considered was variability in underlying musculoskeletal tissue – such as grip strength, band tightness, and forearm circumference. However, there are only low correlations (|R|<0.3) with anthropometric variables. ANOVA indicated age based differences in variability, but no gender based differences. These results are summarized in Fig. 6.

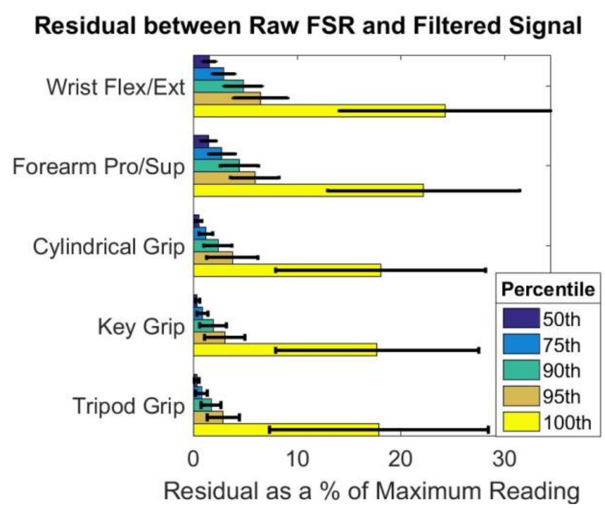


Fig. 4. Summary of FMG variability during dynamic tasks.

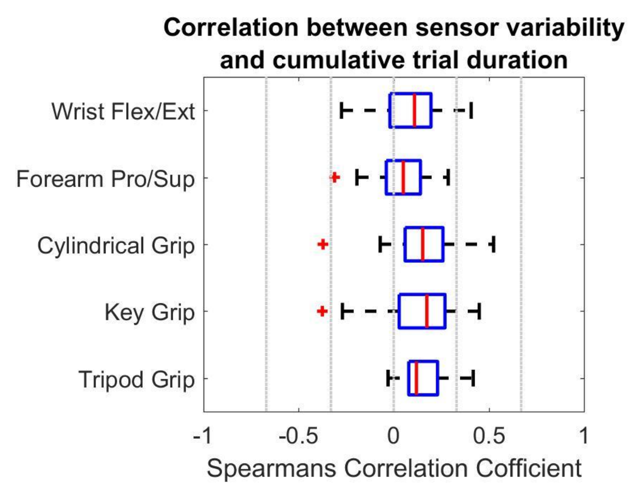


Fig. 5. Correlation between variability and cumulative trial duration. Note: Grey lines indicate -0.67, -0.33, 0.33, 0.67 correlation values.

TABLE II. MEAN VARIABILITY OF WRIST AND FOREARM ANGLES THROUGHOUT RANGE OF MOTION AND RANGE OF EFFORT

| | **Wrist Flex/Ext** | **Forearm Pro/Sup** |
|---|---|---|
| | degrees | degrees |
| Dynamic Wrist Flex/Ext | -- | 4.22 (2.02) |
| Dynamic Forearm Pro/Sup | 4.95 (1.81) | -- |
| Cylindrical, squeeze & relax | 3.00 (0.89) | 2.46 (0.94) |
| Key, squeeze & relax | 3.14 (1.92) | 2.06 (0.88) |
| Tripod, squeeze & relax | 3.16 (1.51) | 2.47 (1.42) |

*Values are presented as μ ($\sigma^2$), where μ is the mean and $\sigma^2$ is the standard deviation*

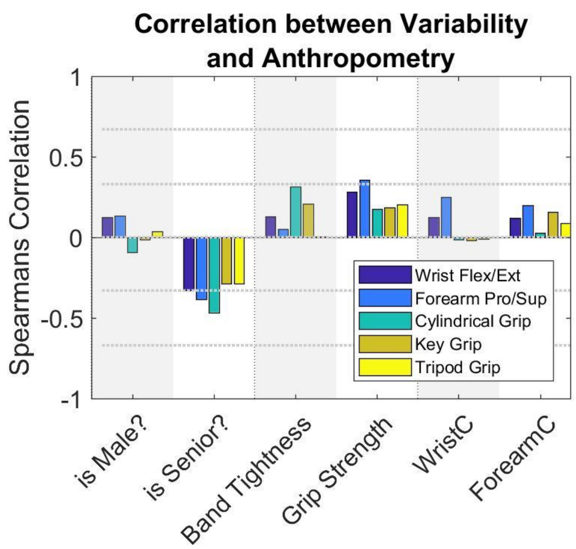


Fig. 6. Correlation between FMG variability and intrinsic variables. Note: Grey lines indicate -0.67, -0.33, 0.33, 0.67 correlation values.

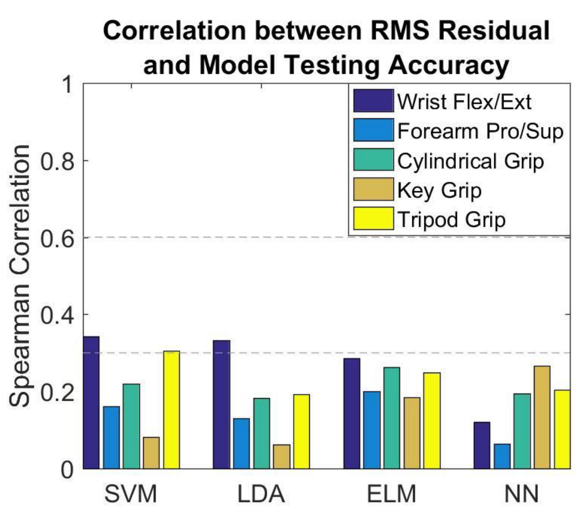


Fig. 7. Correlation between FMG variability and static machine learning model testing accuracy. Note: Grey lines indicate -0.67, -0.33, 0.33, 0.67 correlation values.

## *B. Affect Variability on Machine Learning Testing Accuracy*

The effect of signal variability on FMG model accuracy was also considered. For classification of static gestures, FMG variability presented low (|R|<0.3) to no correlation with the testing accuracies observed. These results are summarized in Fig. 7.

# IV. LIMITATIONS AND FUTURE RESEARCH

Given the results of this work, there are several areas of further research that would benefit from the continued study of FMG. One would be further exploration of anthropometric features and their effect on FMG. In the same lane as this, increasing the recruitment pool of participants for a wider sample of anthropometric features is prudent. This would be significant as restricted data ranges have been shown to have a direct and negative influence on the correlations results [30]. Further work exploring the variability of FMG during repetitive and non-static activities would also benefit from exploring unconstrained activities. An example of an unconstrained monitoring would be tracking upper extremity movement during activities of daily living. Lastly, an avenue of further study should seek to collect data simultaneously from other myographic sources for a more comprehensive comparative analysis such as in [18].

# V. CONCLUSION

In movement tracking and gesture recognition FMG is more frequently being adopted as a myographic technique due the multiple advantages that FMG, particularly FSR based FMG, has over other myographic modalities. Previously, FMG was demonstrated to be stable during statically held gestures, more stable than the traditionally used sEMG. The aim of this study was to explore the stability of FSR based FMG during non-static repetitive motions. Twenty-one participants were recruited to complete five tasks whilst wearing the FMG band. These five tasks required the participants to move between two extremes motion (i.e. full wrist flexion to full wrist extension) or between two extremes of effort (squeezing and relaxing a specific hand gesture). FMG demonstrate low variability (<6%), and appeared to be robust to skin relaxation and variables of anthropometry. Lastly, measured variability demonstrated no significant influence on the performance of machine learning model testing accuracy. The results of this study support the stability FMG during dynamic tasks as well as its continued implementation into user interface technology.


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