Towards Enhanced Control of Upper Prosthetic Limbs: A Force-Myographic Approach

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***Abstract*— Reliable decoding of a user's intention is a key step to control prosthetic devices. Force myography (FMG) is often used to assess topographic force patterns resulting from volumetric changes of activated muscles. However, during limb position changes this approach may give deteriorating performance over time. To address this limitation, we developed a position-aware platform that integrates an inertial measurement unit (IMU) and a force sensing array (FSA) with an advanced signal processing module. The module analyzes data using an artificial neural network (ANN) to predict an intended hand movement. Our results demonstrate that by utilizing multi-sensory information this decoding strategy provides a 90% accuracy.**

I. INTRODUCTION

Development of upper-limb prosthetics has witnessed a resurgence since the Defense Advanced Research Project Agency (DARPA) Revolutionizing Prosthetics program in 2006 [1]. Advances have been made in revolutionary multi-joint mechanical limbs to 3D-printed prosthetic hands [2], [3]. Nevertheless, significant challenges remain in prosthetic design and control for them to be well accepted and integrated into daily life. One such difficulty is reliability and integrated user friendly control interfaces [4].

Currently, surface electromyogram-based (sEMG) systems are commonly used to control prosthetics [5]. This technique involves recording from voluntary muscle co-contractions to infer the intended action. This type of pattern recognition approach has been demonstrated to be effective in many applications including targeted muscle reinnervation, brain-computer interfaces and two-handed gripper control [6], [7]. Although sEMG decoding is often successful in controlled laboratory experiments, there exists a large inconsistency between laboratory results and those observed in realistic clinical setting [8], [9]. Due to control issues, it is estimated that only 25-56% of upper limb amputees choose to wear a prosthetic [10]. A key difficulty is the time-varying nature of sEMG patterns resulting from different limb positions, muscle recruitment, and electrode displacement [11]–[13].

An alternative to upper limb prosthetic control is the application of topographic force mapping (TFM) or force myography (FMG) [5], [12]. In FMG, a pressure sensor array is used to characterize generated force maps due to muscle activities. FMG has been demonstrated to successfully classify different grasp types in able-bodied subjects [14].

Although FMG shows promise as a candidate for human machine interface (HMI) [5], it does not provide robust and consistent results in the presence of non-stationary muscle activity. Therefore, it requires modification to be effective outside controlled experiments. An issues affecting usability is the so-called "limb-position effect," where a change of position of the limb during daily use degrades performance of the prosthetic device. Therefore, to improve the range and functionality of prosthetics, pattern recognition strategies must compensate for changes in limb positioning.

An approach to address the limb-position effect is to increase the relevant environmental information available to the control system [15]. For example, inertial measurement units (IMUs) have been effective for improving static classification outcomes with sEMG [16]. In this study, we develop and apply an IMU integrated FMG system and assess classification performance under different conditions. Our method is a position-aware classification scheme, which is effective for overcoming position-dependent variations.

This paper is structured as follows. Section II provides an outline of the system, description of the sensor design and experimental setup. Section III presents the results of applying FMG under different conditions and a discussion of the important findings. Section IV provides a summary of our work, highlights the significance and provides future directions.

II. MATERIALS AND METHODS

A. Cuff and Sensor Layout

An integrated cuff design was utilized to facilitate the acquisition of hand position data and force myographic signals. The setup included a blood pressure cuff, a force sensor array, and an IMU to estimate the hand position. The IMU and the force sensor array were embedded into the anaeroid sphygmomanometer. This configuration allows the primary forearm muscles to be fully encompassed for signal recording. The experimental setup is depicted in Fig. 1.

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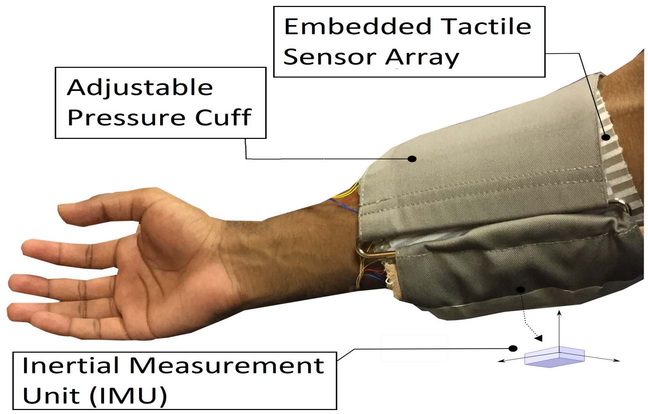

Fig. 1. Sensorized cuff for recording acceleration and force data.

The force sensor array was comprised of a piezoresistive fabric material (Stretchy Piezo LTT-SLPA-150k, Eonyx, USA) which was positioned between two conductive layers (Silver plated mesh, LessEMF, USA), creating a 16×8 mesh of force sensitive taxels. A layer of fusable stretch-cotton (Vilene G785, Vlieseline, Germany) was used to protect the exterior of the sensor and preserve the circuit integrity. Using this architecture, force and pressure values can be detected by measuring the sensor impedance.

Hand position was estimated by collecting the acceleration data using a 3-axis accelerometer (MMA7361L). The IMU was attached to the lower compartment of the sphygmanometer covering the upper part of the dorsal forearm. The IMU and the force sensor array were positioned in parallel to synchronize the FMG and position measurements.

B. Data Acquisition

When a subject was fitted for an experiment with the cuff suitably pressurized, this array was able to record volumetric changes along the upper half of the dominant forearm. In addition, the relative position of the forearm was recorded simultaneously during FMG acquisition. The pressure sensor array was scanned at 20 Hertz using a mbed microcontroller (mbed LPC1768 ARM Cambridge, England). The accelerometer data was collected using an Arduino microcontroller (UNO R3) at 20 Hertz frequency.

C. Population and Experimental Protocol

In this study, 3 healthy male subjects were recruited. The subjects were between 20 to 23 years of age and had no prior experience with force myography or prosthetics. Each subject was fitted with the sensor cuff on the dominant forearm and pressurized to a comfortable but secure level to prevent slippage. The volunteers were asked to perform eight gestures (Fig. 2): (1) wrist flexion, (2) wrist extension, (3) supination, pronation, (4) open hand, (5) power grip, (6) pinch grip and (8) rest. Each gesture was performed from nine different positions ranging from $[-90°, 90°]$ relative to the subject's forearm and parallel to the floor (Fig. 3). For each gesture, 10 co-contractions were performed at each angle. The time required to perform all gestures at all positions

Fig. 2. Illustration of various poses.

was approximately one hour. The subjects were given a ten minute rest period between each angle to prevent muscle fatigue. The experiment was performed through the use of a graphical interface. The interface provided visual feedback to the subjects to help guide them to each designated position and grasp type. Data acquisition was automated by computerized cues instructing the users to contract to a desired grasp, maintain the configuration then relax the muscles to end the co-contraction.

D. Data Analysis

The raw FMG signal was composed of 128 sensor values representing each taxel of the sensor. Measured force data was transformed into a lower dimensional signal using principle component analysis (PCA) [17].

PCA was performed after subtracting the signal mean and computing the singular value decomposition of the signal covariance matrix $X^T X = U \Sigma V^T$. Since Σ is a diagonal matrix of eigenvalues, the matrix can be truncated to remove

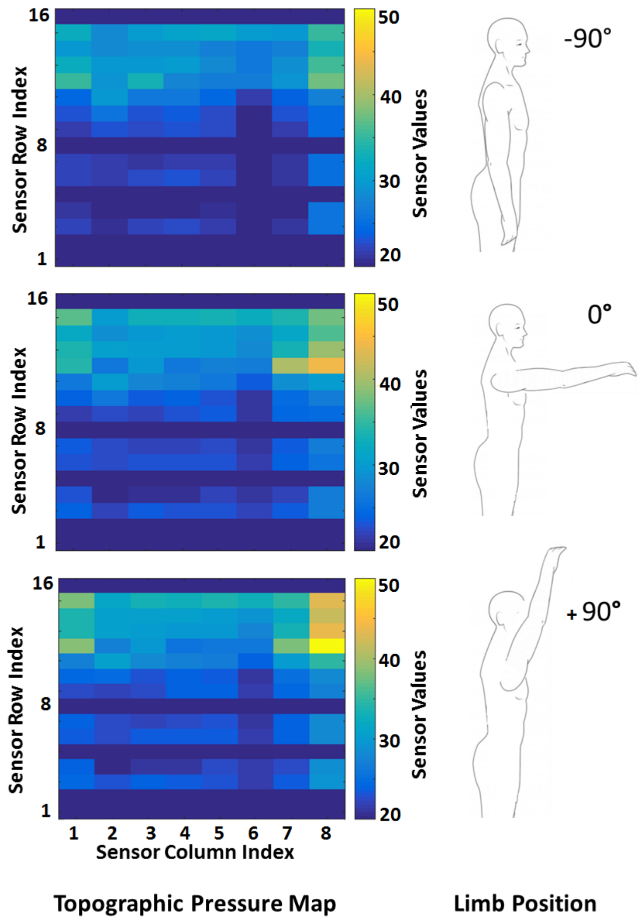

Fig. 3. Force maps of resting hand at -90°, 0°and +90°. Sensor measurements were recorded at eight pose locations (only three are shown).

components that contribute little to the observed variance of the dataset. This is done by considering only the most significant eigenvalues. In our application the 95% confidence bound was selected to capture components that are the most meaningful for pose discrimination. Hence, PCA was used to remove redundant dimensions and make the dataset suitable for further analysis. This has the benefit of simplifying the signal and avoids overfitting by a classifier.

Lower dimensional data were used as inputs to an artificial neural network (ANN) for classification of forearm pose. An ANN was chosen for its simplicity and ability to classify non-linear signals [18]. In our study, a 2-layer feedforward neural network was utilized. The hidden layer consisted of ten neurons. Backpropagation was implemented with conjugate gradient descent optimization. The network was trained and validated using 5-fold cross validation.

To characterize and compare our proposed position-aware strategy with position-unaware approaches, we used three different network architectures as follows.

1) *Position-Unaware Individual Classifier*: Classifier was trained using data collected from one position.
2) *Position-Unaware Aggregate Classifier*: Classifier was trained using data from all available positions.
3) *Position-Aware Ensemble Classifier*: An ensemble classifier was constructed. The ensemble consisted of several position-unaware parallel classifiers each trained using data collected from a specific hand position. The classification outcome was based on a Bayesian data fusion approach. This technique uses outputs of the position-unaware classifiers fused with a position-dependent Gaussian kernel. Let N_c be the maximum number of position angles and N_p the maximum number of poses. The probability of pose i occurring $(\Pr(p_i))$ can be calculated as the marginal probability over classifiers in all possible positions as

$$\begin{aligned} \Pr(p_i) &= \sum_j \Pr(p_i|C_j)\Pr(C_j) \qquad (1) \\ \text{for } i &= 1,2,\ldots,N_p \quad \text{and} \quad j = 1,\ldots,N_c \end{aligned}$$

where C_j denotes a classifier trained for a predefined position and $\Pr(C_j)$ indicates the probability that the chosen classifier is correct. We estimate the $\Pr(C_j)$ using a Gaussian kernel

$$\Pr(C_j) = \exp(-(\hat{\theta} - \theta_j)^2/2\sigma^2) \qquad (2)$$

where θ_j is the angle classifier C_j was trained with, and $\hat{\theta}$ and $\hat{\sigma}^2$ are the position and variance estimates of the IMU, respectively. The predicted pose is then determined using the following criteria

$$\text{Predicted Pose} = \underset{\forall i}{\text{argmax}} \ \Pr(p_i) \qquad (3)$$

III. RESULTS AND DISCUSSION

A. Limb Position Effect

To assess the efficacy to detect intended movements from measured force patterns, we trained and tested a classifier for each measured position. When the classifier was trained and tested for the same position, it achieved an average classification accuracy of 97%. However, when the classifier was tested with data from other positions, the accuracy dropped significantly. The average classification accuracy was 30.9±4.1%.

We denote this phenomena as the limb position effect. A classifier trained at a specific position has reduced predictive capability when the prosthetic arm moves from its location of intended use. This effect can be observed in Fig. 4 where two confusion matrices are shown at different positions. Although the matrices on the left indicates highly accurate classification can be achieved at a given limb position when it is also trained at the given position. However, the matrices on the right show a significant reduction of accuracy for a classifier trained at 0°but tested at other positions. The drop in accuracy and inconsistent classification suggests the FMG signals are notably different at each position.

To characterize this effect, we measured the accuracy as a function of distance of the test and training positions (angles). The results are presented in Fig. 5, which illustrates the accuracy for a classifier trained at 0°position and tested with data from other positions. The results demonstrate that the accuracy decreases rapidly when the position is changed

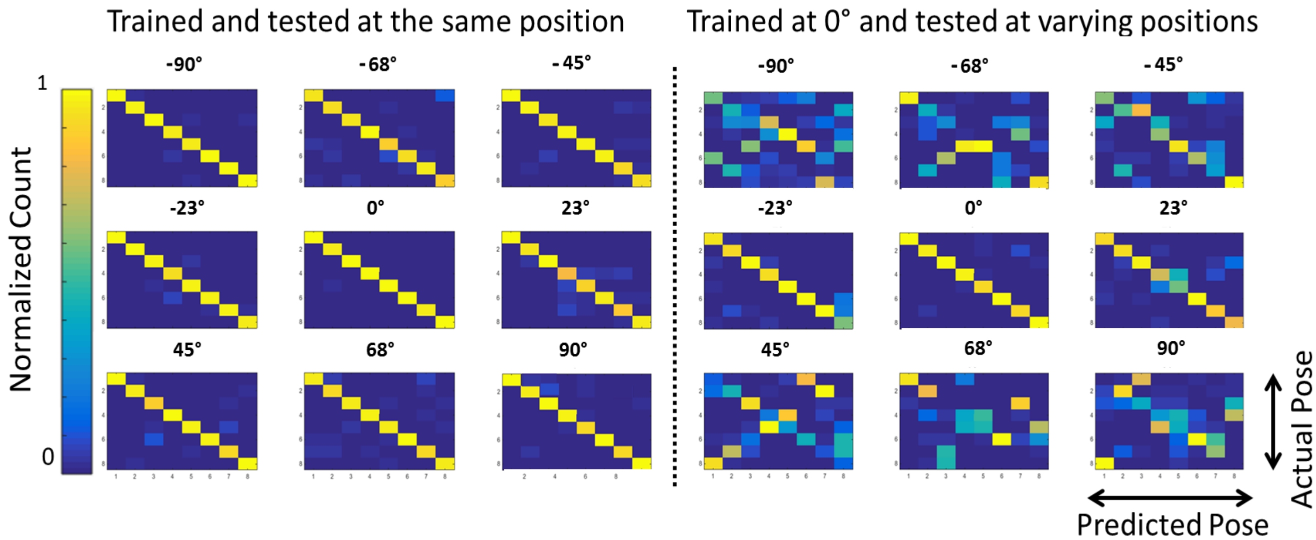

Fig. 4. Confusion matrices for individual position-unaware classification. Left: Classifiers trained and validated at the same positions. Right: Classifier trained at 0° and validated at all positions.

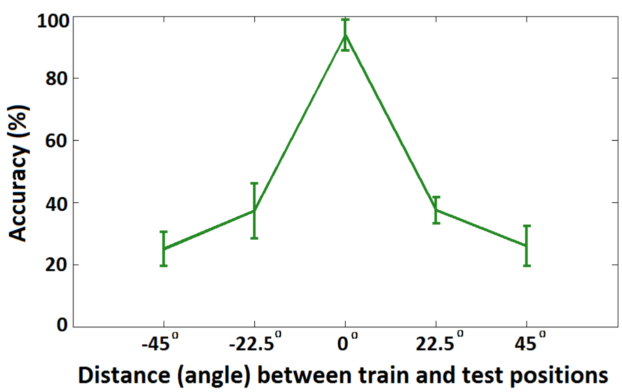

Fig. 5. Classification accuracy versus distance (angle) of the test and training positions.

from the training position. This indicates that the method is highly data-dependent.

A possible approach to reduce this effect is to train the system with data from all configurations. Implementing this strategy, the system was able to achieve a classification accuracy of 72.9±3.8%. Although this strategy results in improved accuracy and reliability, it demands extensive training for all possible data combinations, an expensive and time consuming task.

B. *Position-aware classification*

We investigated the effectiveness of using multi-sensory data to overcome limb position effect to improve classification accuracy and reliability. We used position data in combination with force data to develop a position-aware ensemble classifier (see §II-D). This method improves classification accuracy by using the most suitable classifier for each dataset. Using this strategy, the classification accuracy was improved to 89.4±4.2%. Moreover, it has the ability to extrapolate data points to obtain classification outcome for untrained positions.

TABLE I
CLASSIFICATION RESULTS AMONG 3 SUBJECTS

Technique	Subject 1	Subject 2	Subject 3
Individual Classifier	30.2±4.6%	30.8±3.5%	31.6±3.3%
Aggregate Classifier	71.4±2.2%	74.9±5.0%	72.3±3.4%
Ensemble Classifier	88.4±7.5%	91.8±1.6%	88.1±4.8%

A comparison of the classification accuracy for position-unaware classifiers and the position-aware ensemble classifier is provided in Table I and Fig. 6.

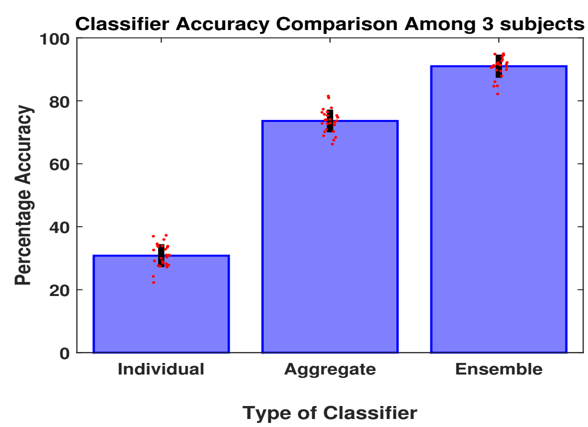

Fig. 6. Comparison of three classification methods. Data is pooled among all 3 subject in this study.

The results demonstrate that the highest classification accuracy is achieved when limb positions are also utilized.

IV. CONCLUSION AND FUTURE WORK

In this study, we investigated the suitability of force-myography for classification of intended hand movements for prosthetic applications. We demonstrated the applicability of this method with experimental data. We also developed a technique to compensate for limb position effect using a multi-sensory approach. A position-aware ensemble classifier was developed by fusing limb position information and force signals. Limb position was estimated using data from a 3-axis IMU. Using this strategy, we achieved robust and reliable classification accuracy for varying limb positions. The average classification accuracy across 3 subjects was improved from $30.9\pm4.1\%$ to $89.4\pm4.2\%$. Although a neural network can be trained with a larger number of samples to predict untrained cases, it requires long training times. The ensemble classifier helps alleviate this problem by using a simpler position-specific structure.

In future work, we will investigate the suitability of position-aware ensemble classifiers to be generalized for untrained cases. This method has the advantage of requiring less training samples. Therefore, it may be a practical alternative for systems that cannot be trained for all possible datasets.

In addition, we will consider dynamic scenarios where a motor control command is evoked while the limb is moving. Such dynamics often elicit non-stationarity which are, for example, due to change of force patterns as a result of large loads, degradation of signal acquisition and muscle fatigue [19]. This requires the development of methodology that is invariant to non-stationary data. In addition, these techniques will be evaluated on amputees instead of able-bodied individuals.

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