Optimization of EMG Movement Recognition for Use in an Upper Limb Wearable Robot

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Abstract— **To functionally aid patients suffering from neurological disorder, a 3 degrees-of-freedom (DoF) upper limb wearable robot is presented (Fig. 1). In order to provide seamless user assistance, the intention of the wearer must be determined. As a sensing mechanism, electromyographic (EMG) signals have commonly been used to estimate human movement. In this study, the effectiveness of movement recognition using a generalized 8-port EMG sensor (Myo Armband) around the forearm was evaluated. Four fundamental movements of the arm (wrist flexion/extension and forearm pronation/supination) were classified using a neural network (NN) with a single hidden layer. The classification method was optimized through analysis of pre-processing algorithms and window size (0.25 to 1 second) to reduce computational expense and maintain classification accuracy. Through these accomplishments, significant groundwork has been provided for the development of a robust and non-invasive solution to tremor of the upper limb.**

I. Introduction

Neurological movement disorders such as Parkinson's disease cause many debilitating symptoms. One of the most common symptoms is tremor, which can cause difficulty with even the simplest activities of daily living [1]. Treatment for severe tremor typically involves pharmaceuticals or invasive surgeries such as thalamotomy or deep brain stimulation [2, 3]. Each of these therapies may cause side effects including large motor fluctuations, dyskinesia and psychiatric issues [4]. As non-invasive solutions, biomechanical therapies and resistance training have effectively reduced tremor [5, 6]. Successful research in this area has led to the potential for constant therapy for tremor through a wearable robot.

Wearable robotic exoskeletons have typically been developed either to increase the strength and endurance of healthy individuals, or to enhance motion of the disabled or injured [7]. The prior application is particularly attractive for military or industry [8] while wearable robots for rehabilitation have typically focused on the lower limb and aiding gait [9]. Some wearable robots have been developed for the arm as well, but the increased complexity of the upper limb presents many unique challenges.

The problem of aiding the daily lives of tremorous individuals is distinct from either of these applications. In this case, motions which are involuntary should be eliminated, while voluntary movements should be enhanced to account for muscle stiffness and weakness, which are also common symptoms of neurological disorders. Wearable robots such as the WOTAS have been developed to address these challenges [10], but are still too heavy and bulky to be worn in daily life.

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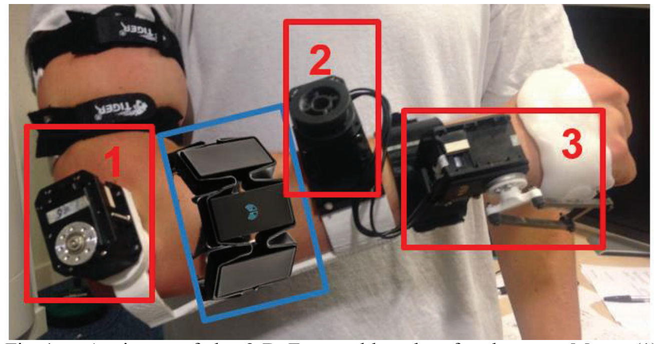

Fig. 1 A picture of the 3-DoF wearable robot for the arm. Motor (1) controls elbow flexion/extension; (2) controls forearm pronation/supination through cable transmission; (3) controls wrist flexion/extension through a parallel linkage. The blue box indicates placement of the Myo Armband.

To aid patients with tremor, two distinct foci should be considered. First, a suitable method of classifying voluntary movement in multiple degrees of freedom (DoF) needs be determined. This classification scheme can later be translated to control motor movement in the proper DoF. Second, a novel and adaptable mechanism of tremor suppression, involving the modeling and characterization of tremor and a control scheme to minimize this in patients. This paper focuses on the first aim.

Much research has gone into arm movement classification using EMG [11], with many papers geared toward wearable robots [12, 13]. However, many of these trials relied on precise placement of EMG electrodes on specific muscles [13, 14], which isn't convenient for a wearable device that can be removable. Previous research used a variety of processing algorithms for features, including mean absolute value (MAV), area under the curve (AUC), zero crossings (ZC), waveform length (WL), and root-mean-square (RMS) [15, 16]. Clancy et. al. [16] compared the performance of RMS with MAV, but did not include other potential processing techniques in the study. After using these methods to extract features, recognition of desired motion patterns still requires a classification mechanism. Groups have previously used neural networks (NN), fuzzy logic, probabilistic models, and muscular models to classify arm movements [11-13].

This paper compares several pre-processing methods to determine their contributions to classification of four fundamental movements of the lower arm, and investigates the effect of window size on classification accuracy. Using the found optimal parameters to select features as input to a neural network, classification of 6 subjects' lower arm movements ensues. A successful classification mechanism can then be incorporated into the control of the designed wearable robot.

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II. Wearable Robot: System Overview

The wearable robot that was designed to aid patients with tremor consisted of 4 main pieces which each corresponded to an anatomical part of the arm. The hand, wrist, forearm, and upper arm each had a 3D-printed rigid segment made of ABS plastic associated with them. Each of these pieces was held on by straps that were placed based off of anatomical landmarks. The robot moved in 3 DoF corresponding to wrist flexion and extension, forearm pronation and supination, and elbow flexion and extension, respectively (Fig. 1).

To capture data on the intended movement of the wearer, a Myo Armband with 8 EMG sensors was placed around the widest part of the forearm, collecting data at approximately 200 Hz. While this particular armband will likely not be used in future designs of the wearable robot, it serves as a proof of concept for the processing algorithms. The armband also collects orientation data from accelerometers and gyroscopes, but this was not used during this study.

III. Methods

A. Pre-Processing

The method used in this paper for determining the intended movement of the wearer relied on the assumption that any lower arm motion can be broken into some combination of four fundamental movements: 1) Wrist flexion; 2) Wrist extension; 3) Forearm pronation; or 4) Forearm supination. These movements occur in the same DoF as the two distal motors of the wearable robot, so classification in this way can later be directly translated to motor movement. These movements were also classified against 5) No movement, which served as a fifth output.

Movement classification was carried out through the collection of EMG data from a Myo Armband. The data was pre-processed in several ways in a sliding window of w=50 data points, or approximately 0.25 seconds. The MAV, AUC, ZC, WL and a smoothed resultant vector combining all 8 raw signals were all used to determine which type of movement was occurring [18]. The calculations for each of these are shown in Fig. 2.

10 features were extracted from each EMG port for each overlapping window of time. The maximum and average of MAV, ZC, and WL signals for each port were all selected as features, as well as the maximum, minimum, range, and time difference between maximum and minimum for AUC. This resulted in a total of 72 potential features for each overlapping window, as one EMG port was defective and 2 features were reserved for the maximum and average of the resultant signal. Each feature was normalized by the overall range of values.

B. Optimization

To optimize the performance of the neural network, a preliminary study was carried out to find the most suitable features among those described above, and to determine the effect of window size on classification accuracy. While multiple pre-processing methods could feasibly be used at the same time to maximize the number of features as inputs to the network, this may not be desirable for real-time applications when a similarly accurate network is faster.

$$MAV\ (i,j) = \frac{1}{w}\sum_{n=i}^{i+w} \left|EMG_{n,j}\right| \qquad [1]$$

$$AUC(i,j) = \sum_{n=i}^{i+w} EMG_{n,j} \qquad [2]$$

$$ZC(i,j) = \sum_{n=i}^{i+w} \left[f_{zc}\left(EMG_{n,j} - EMG_{n-1,j}\right)\right] \qquad [3]$$

$$where\ f_{zc}(x_n) = \begin{cases} 1, & if\ x_n > EMG_{n,j} > 0\ OR\ x_n < EMG_{n,j} < 0 \\ 0, & Otherwise \end{cases}$$

$$WL(i,j) = \sum_{n=i}^{i+w} \left|EMG_{n,j} - EMG_{n-1,j}\right| \qquad [4]$$

$$Resultant(i) = \sqrt{\sum_{j=1}^{8} EMG_{i,j}^2} \qquad [5]$$

Fig. 2 Calculations for each of the pre-processing methods for EMG data: Mean Absolute Value (MAV), Area Under the Curve (AUC), Zero Crossings (ZC), Waveform Length (WL), and the Resultant signal of all 8 EMG ports. All equations were carried out in a window size of w=50. i is representative of a point in time, while j represents each EMG channel.

MATLAB and Neural Designer were the software used to carry out the optimization, with MATLAB selecting features for each time point based on the pre-processing method and window size. The amount of window overlapping was inversely modulated with changes in window size to account for any discrepancy in the amount of training data. This ensured that no matter what type of preprocessing occurred, each trial could be mapped to the same output matrix.

For preliminary data collection, 3 subjects performed 10 cycles of wrist flexion and extension and 10 cycles of forearm pronation and supination while wearing the Myo Armband on the largest part of their forearm. The resultant data was then visually classified by a researcher with knowledge of each task and fundamental movement. The preprocessed data were then loaded into Neural Designer with the corresponding output matrices and used to train the network, with 60% of the data used for training, 20% for selection, and 20% for testing. A regularization value of 0.005 was used for all trials.

C. Movement Classification

6 healthy subjects performed a pre-defined set of tasks comprised of the four fundamental movements of interest. These tasks were defined to be 1) 10 cycles of wrist flexion and extension (FE); 2) 10 cycles of forearm pronation and supination (PS); 3) 5 cycles of wrist flexion and extension, then forearm pronation and supination (FEPS); and 4) The same movements as (3), but while sustaining each motion for a few seconds before continuing on to the next motion (FEPSH). EMG data was recorded using a Myo Armband with 8 ports as they performed these tasks. All subjects provided informed consent for their participation.

Features were extracted from raw EMG signals and a final classification for each window of time was determined by forward propagation through a neural network. The features selected were based on the results of the optimization testing, Classification results were compared to a visual classification of the same motion data by a researcher with knowledge of each of the fundamental movements and each task. 60% of each data set were used for training, while 20% were used for selection and 20% for testing.

The aptitude of each type of classification was determined through the calculation of overall accuracy, as well as the other classification metrics such as the sensitivity, specificity, and precision (PPV). Comparisons were made depending on the amount of subjects to whom the system was attempting to generalize, and between different subjects, the four fundamental movements, and the performed task.

IV. Results and Discussion

A. Optimization

The optimization study revealed several key pieces of information regarding the implementation of this type of neural network for motion classification using EMG. Firstly, order selection revealed a fourth order system. Therefore, four neurons were chosen in a single hidden layer, with seven preprocessed EMG signals as inputs and five outputs. This configuration was used for the remainder of the study.

As can be seen in Fig. 3, each preprocessing method provided different classification accuracies. For tested features, the average overall classification accuracies were 0.845, 0.660, 0.743, and 0.845 for MAV, AUC, ZC, and WL, respectively. Classification accuracy generally decreased with increasing window size for nearly every pre-processing method. The one exception is AUC, whose performance was poor throughout the testing. While MAV showed the best performance with smaller window sizes, when the window was increased to 200 data points, WL was move predictive.

Other considerations for window size were which movements were accurately predicted. While overall performance dropped with increased window size, correct classification of supination was lowest with a window size of 50 (0.25 s), and increased for window sizes of 100 (0.5 s) and 200 (1 s). For MAV, supination's classification accuracies were 0.535, 0.692, and 0.673, respectively.

Preliminary testing also showed which types of features should be chosen for each of the pre-processing methods. The maximum and average of a pre-processed signal were the most commonly chosen features, and were directly compared for MAV, as can be seen in Fig. 4. Maximums

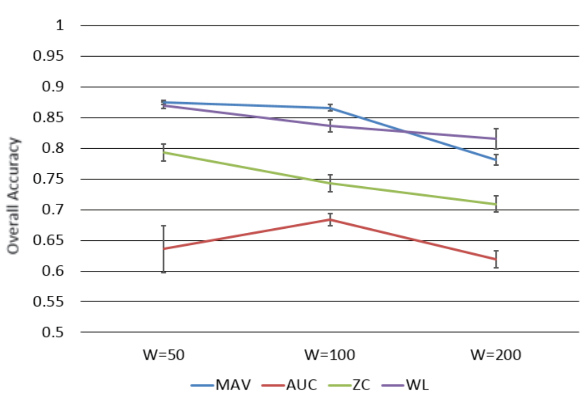

Fig. 3 Performance of each of the pre-processing methods for EMG data in different window sizes (W). Mean Absolute Value (MAV), Area Under the Curve (AUC), Zero Crossings (ZC), and Waveform Length (WL) were the pre-processing methods evaluated. The bars represent standard error.

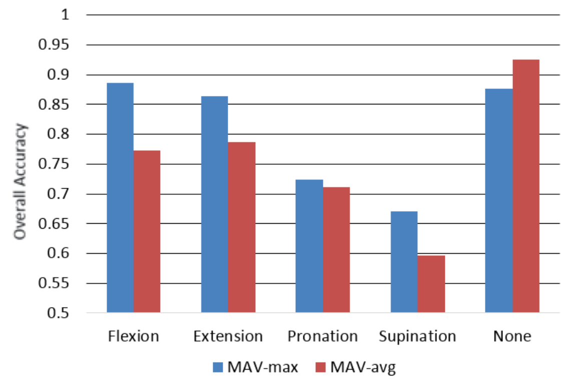

Fig. 4 Comparison of maximum (blue) and average (red) features for mean absolute value (MAV) pre-processing. While averaged features were more predictive of no movement, maximums predicted movements more accurately.

showed more accurate classification for every one of the fundamental movements, while average values were able to predict the absence of movement more accurately. This is reasonable, considering selecting for maximums would more likely guess dynamic movements in pre-processing methods with positive values. With these results in mind, the final features chosen to be used for motion classification were the maximums of MAV processed with a window size of 100.

B. Movement Classification

Using the optimized features as presented above, the neural network showed an overall classification accuracy of 76 percent when attempting to generalize to 6 different subjects. As seen in Fig. 5, there was a decrease in system performance as the system attempted to generalize to more subjects. These results may indicate that this neural network model does not generalize particularly well for a wide range of individuals, and therefore each different subject needs to provide sufficient training data to maximize performance.

When classifying movements for a single subject, the network achieved a maximum over 90 percent accuracy. Fig. 6 illustrates a logarithmic correlation between the amount of training data each subject provided and the overall accuracy for that subject. Therefore, some of the decreased performance seen in Fig. 5 may be due to the inadequacy of training data for later subjects. It is also possible that the performance decreased due to quicker movement speed, which is generally what affected the size of each subject's data.

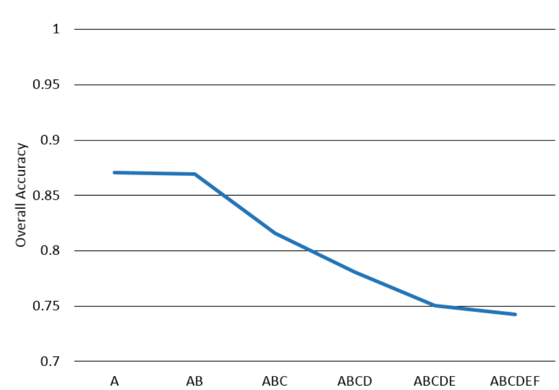

Fig. 5 Overall classification accuracy for the NN across 6 subjects. Accuracy decreased when the network tried to generalize to more subjects.

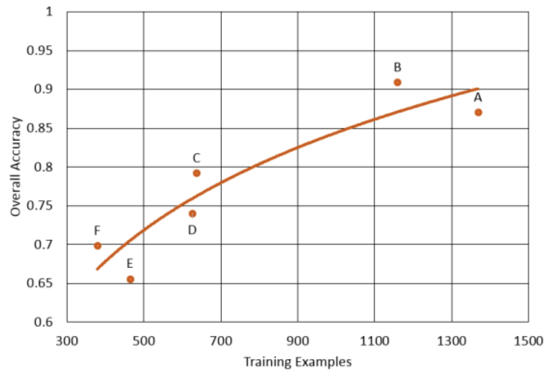

Fig. 6 Performance metrics for classification, organized by the nature of the task that was performed: These values are for subjects A and B only. The FEPSH task had the lowest value in every classification metric.

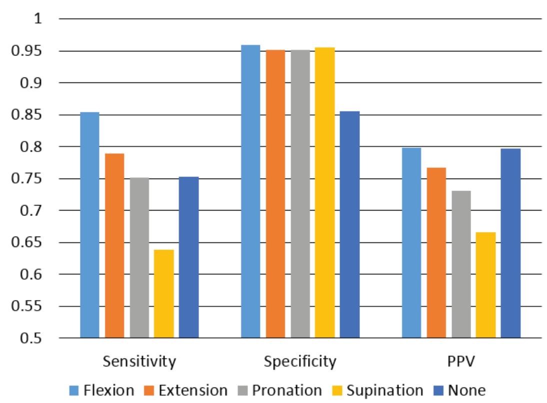

Fig. 7 Performance metrics for classification, organized by each one of the fundamental movements: Flexion (F), extension (E), pronation (P), supination (S), and the absence of movement (None).

Each fundamental movement appeared differently in terms of the classification metrics, as can be seen in Fig. 7. All of the fundamental movements showed a specificity above 0.95, while the specificity of detecting no movement was closer to 0.85. This indicates that false positives are most common in cases where no movement is expected when the wearer intended to move. Sensitivity and precision decreased together, with the highest value being flexion, then extension, pronation, and supination. Sensitivity was slightly higher than precision in general, which indicates that false positives may present more of a problem than false negatives.

There was little variation in classification accuracy depending on the task performed. Overall accuracy was consistently within 1 percentage point of 76.7% for all types of tasks. The tasks were similar in terms of each of the classification metrics as well, though FEPS showed the lowest sensitivity (0.6959) when compared to FEPSH (0.7696), FE (0.7777), and PS (0.7318).

Overall, the classification of four fundamental arm movements using a neural network was successful, though improvements could certainly be made by improving the training data. Ideally, a good general model should be created that is able to be easily trained with a small amount of patient-specific data. Training with more data should especially improve classification of forearm pronation and supination, as these movements are still most likely to be misrepresented.

V. Conclusions and Future Work

This paper investigated the use of a wearable robotic exoskeleton to combat tremor in patients with neurological diseases. A neural network for recognition of fundamental movements of the lower arm was developed, and performance was optimized through feature evaluation. This revealed that the maximums of mean absolute value with a window of 100 (0.5 s) was most accurate. An overall classification accuracy of up to 90 percent for a single subject was achieved, but decreased to 76 percent when generalizing to 6 subjects.

While this work is crucial to the development of a wearable robot, there is still much to be done. Real-time translation of EMG data into motor movement in all DoF should be investigated, as well as the inclusion of different sensors to aid in movement classification. Future studies will explore the best way of training the classification system to a new patient, including determining the proper amount of training data and the utility of pre-training the network.

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