Regressing force-myographic signals collected by an armband to estimate torque exerted by the wrist: a preliminary investigation

Maram Sakr and Carlo Menon, *Member, IEEE*

***Abstract*— Human-machine-interfaces (HMI) have a key role for translating human intention into control commands to external devices. Different wearable techniques, including surface electromyography (sEMG), have been proposed for acquiring bio-signals that reveal the human intention. In this paper, we explore an easy-to-use wearable sensor device that can be used to measure force-myography (FMG) signals. We assess if FMG signals can be used to estimate isometric torque of hand pronation-supination, wrist flexion-extension or wrist radial-ulnar using a regression model. Results of our investigation report an average accuracy over 90%. The related standard deviation of 0.02 is showing consistency of data among different data collecting sessions. The proposed FMG-based device shows therefore promising performance for different future applications, which may include: monitoring the progress of patients during exercising in arm rehabilitation programs; proportional control of robotic hand prosthesis; and control of robot movements.**

Keywords*— *Force Myography; Human Machine Interaction Regression; Rehabilitation Robotics; Wearable Sensors;

I. Introduction

As the field of robotics continues to advance, the focus on the development of the technologies used in the human-machine-interface (HMI) increase. This paper explores the possibility of using an FMG based sensing device for predicting the isometric wrist torque, which could potentially be used in many applications such as rehabilitation programs for stroke survivors, prosthesis technology for amputees, and physical human robot interaction in industrial environment.

All the above applications need to have an HMI that converts the collected biological signals into control signals for the robotic manipulator [1]. Surface electromyography (sEMG) signals for motion estimation are proposed to be used for controlling the prosthesis [2], upper limp rehabilitation [3, 4] and for human machine cooperation [5]. However, sEMG signal requires expensive and sizable equipment as well as a high-level signal processing for feature extraction. In contrast, Force Myography (FMG) signals can be a better technique in terms of cost and complexity. Recently, FMG signals have been used for proportional grip control of robotic prosthesis [6, 7]. Moreover, they are used to detect the fingers forces [8], finger motion recognition [9] and arm position recognition [10].

In this paper, we propose a novel FMG system to estimate the isometric wrist torque using an easy-to-use strap with multiple force sensing resistors (FSRs) for capturing the FMG pattern. The FMG signals are processed using support vector regression (SVR), to predict the exerted isometric torque. Two studies are carried out to explore the potential of the system as well as to evaluate the system's performance.

II. Experimental setup

A. Force sensing resistor (FSR) band

In order to extract the FMG pattern related to the exerted torque, we used a band that has a custom fabricated sensor strip composed of 16 force sensitive resistors (FSRs), 0.66 inch apart from each other. Velcro tapes are placed on both ends of the strap to tie it onto the user's forearm. This band has an Arduino pro mini kit and a Bluetooth module to transfer the data.

A voltage divider circuit is used for quantifying the FMG signals from FSRs. The base resistor in the voltage divider circuit controls the sensitivity of the FSR, which is empirically set to 22 K Ohm in this study. The voltage divider circuit is powered by a 5v battery, which is embedded into the strap. The resistance of the FSRs is inversely proportional to the applied force. At the initial stage, the resistance of the FSRs is more than 100 K Ohm, and it decreases exponentially as the applied force increases.

B. Custom rig

We study the feasibility of using the FMG signals for predicting the isometric forearm/wrist torque on three different setups separately. Each setup is designed to collect a different type of data. The first setup is used for collecting forearm pronation-supination deviation. As shown in Fig. 1, the setup consists of two aluminum plates with a torque sensor (Transducer Techniques TRT-100) connecting them to each other. One of these plates holds a handle where its axis of rotation is aligned with the sensor's axis of rotation. While the other plate is fixed to a table.

The second setup is used for collecting wrist flexion-extension variation. As shown in Fig. 2, the setup is mainly

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M.Sakr is with the MENRVA Group, School of Engineering Science, Simon Fraser University, Burnaby, BC V5A 1S6 Canada (e-mail: msakr@sfu.ca).

C.Menon is with the MENRVA Group, School of Engineering Science, Simon Fraser University, Burnaby, BC V5A 1S6 Canada (e-mail: cmenon@sfu.ca).

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Fig. 1. The setup for collecting pronation-supination data.

comprised of two parts: a base that allows the user's forearm to rest on and an aluminum plate for holding the user's hand with the help of Velcro tapes. The same torque sensor is placed on the right side of the hand, align with the main axis of the applied torque.

The third one is used for collecting radial-ulnar movements of the wrist. This setup is similar to the previous setup except that the torque sensor is placed under the wrist to capture the wrist radial and ulnar deviations.

The torque sensor in each setup is connected to an amplifier to adjust the sensor's output and increase the sensitivity of the sensor. The amplifier is connected to a data acquisition (DAQ) device from National Instruments (NI USB 6210) interfaced with a custom LabVIEW software to read the data.

C. A. Data collection protocol

First, the torque sensor's amplifier is calibrated using pre-defined weights, to get the calibration equation that maps the amplifier readings to the torque values in Newton meters (Nm). The band is placed on the belly muscles of the forearm during the data collection sessions. The experiment consists of three sessions for each setup, every session lasts for one minute as the participant feels a fatigue in the forearm muscles when exerting the maximum torque repeatedly. The data are collected with a sampling frequency of 10 HZ, which means that we gather 600 samples per session and a total of 1800 samples to be collected for each setup.

One healthy volunteer participated in this experiment. The participant signed an informed consent form (approved by the office of Research Ethics at Simon Fraser University). The participant is asked to do a few tasks. First, the participant is asked to pronate and then supinate his/her forearm to the maximum voluntary contraction (MVC) repeatedly. The result is approximately in the form of a sinusoidal wave. This guarantees that the collected data covers the maximum possible range of torque values. This procedure is repeated three times.

Then, the participant rests his/her hand for a while before starting to collect the flexion-extension data using the second setup. The participant then places his/her forearm on the platform of the rig, the wrist on the top of the axis of rotation of the load cell, and the palm on the aluminum plate. The participant's forearm and palm are secured to the custom rig using the Velcro tapes. With this arm position, the data are collected for both of the FMG signals and the flexion-extension isometric torque for three sessions. Fig. 3 shows a sample of the torque signals that have been gathered during one session, for one minute. The number of peaks in the torque graph represents the transition speed between the flexion and extension deviations during the data collection.

Finally, the data are collected for the wrist radial and ulnar deviations using the same arm position used in the previous setup with the third setup, for three periods with each period is one minute long. During the data collection, a visual chart, shows the amount of exerted torque with the shape of the full wave to visually guide the participant throughout the experiment.

All the data acquired from the nine sessions are stored in a file for off-line processing and analysis.

III. Signal Analysis

The resulting datasets are analyzed in order to obtain the accuracy of the proposed device within the outline of the experimental protocol. First, a sensor selection criterion is applied to the sixteen FSR readings to eliminate the sensors that did not capture the FMG signal well, which have a low variability along the data-set. This criterion is basically depends on the size of the participant's forearm.

A. Signal processing

Initially, a moving average filter with a window size of 3 is applied to the torque values to smooth the signal. Subsequently, both of the raw data acquired from the FMG patterns and the torque values are scaled to the maximum value that the sensors can read.

B. Regression

A support vector machine (SVM) method called support vector regression (SVR) is used to handle the regression problem. SVR is one of the high-performance techniques [11, 12, 13] based on a nonlinear generalization of the Generalized Portrait algorithm developed by Vapnik [14]. The LIBSVM library [15] is used for processing the data off-

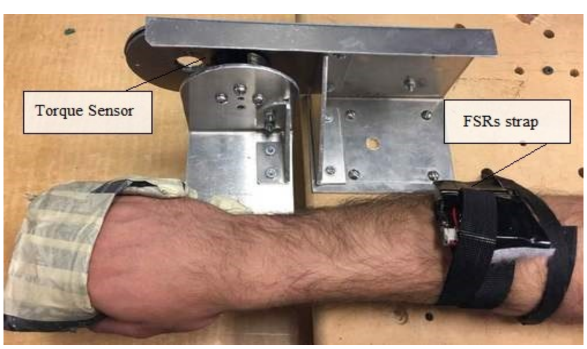

Fig. 2. The setup for collecting flexion-extension data.

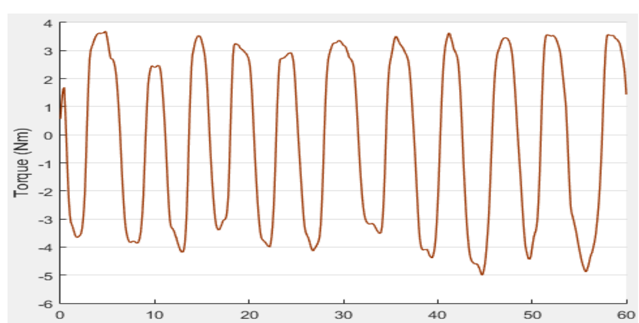

Fig. 3. Sample of the torque signal.

line in MATLAB® environment. We use Nu Support Vector Regression (ν-SVR) [16], as the ν parameter in ν-SVR can be used to control the amount of support vectors in the resulting model, with a non-linear Radial Basis Function (RBF) [17] kernel, as in (1)

$$K(x,y) = e^{-\frac{\|x-y\|^2}{2\sigma^2}} \tag{1}$$

We use 10-fold cross validation to choose the best values for SVR parameters (cost and gamma). Where the average accuracy of the 10 iterations is considered as the metric to compare between the different values for both the cost and gamma, as it is usually done in common practice [18, 19].

Two studies are performed in order to evaluate the possibility of using the FMG signals in predicting the wrist/forearm torque values. The first one aims at studying the feasibility of using the FMG signals through measuring the performance of the trained model for each data type separately and comparing the test accuracy using different training data size.

For the pronation and supination data, the three sets of data from the three sessions are combined to have 1800 samples. Then, the data is randomly divided into 60% for training and 40% for testing. A 10-fold cross validation is performed using the 60% of the training data to choose the best values for the cost and gamma. Then, the 6 SVR models are trained using a different portion of the training data i.e. 60%, 50%, 40%, 30%, 20% and 10%, respectively. Finally, the obtained models are tested with the 40% of the whole data that have been reserved earlier to the testing purposes. The same procedure is repeated with the flexion-extension data as well as the radial-ulnar data.

The second study is to explore the consistency of the FMG patterns through training the model using two data sets from two sessions and test the obtained model with the remaining set from a different session. The idea here is similar to the k-fold cross validation [20] with the exception of dividing the data based on the number of the data collection sessions (repetitions) not on a percentage (random number). Every time one data set is left out for testing purposes while the rest of the data sets are used to train the model. This is done three times which equals to the number of data collection sessions. Then the standard deviation is calculated for the coefficients of determination that obtained from the three repetitions to give us an intuition about the consistency of the FMG patterns through different sessions. The previous procedure is performed with the three data types, forearm pronation-supination, wrist flexion-extension and wrist radial-ulnar.

IV. RESULTS AND DISCUSSION

The normalized root mean square error (NRMSE), and the coefficient of determination (R^2), as in (2), are considered as the indicators of performance for the testing data.

$$R^2 = 1 - \frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \acute{y})^2} \tag{2}$$

Where y_i and f_i are the expected and the predicted torque values, respectively, and $\acute{y}$ is the mean of the expected torque values. The coefficient of determination is the number that indicates how well the trained SVR model fits the data, ranging from 0 to 1. The NRMSE is a dimensionless metric that reflects the difference between the estimated and the expected values. It is represented as a percentage of the torque values exerted by the participant. Its mathematical formula is given in (3):

$$\text{NRMSE} = \frac{\sqrt{\frac{\sum_{i=1}^{N}(y_i - f_i)^2}{N}}}{(y_{max.ulnar} - y_{max.radial})} \tag{3}$$

Where N is the number of samples in the test set. Also, $y_{maxulanr}$ and $y_{max.radial}$ are the maximum ulnar and radial torque exerted by the participant. $y_{maxulanr}$ and $y_{max.radial}$ are replaced by flexion-extension maximum torque, when testing the flexion-extension data and with pronation-supination when testing the pronation-supination data.

The test performance metrics, R^2 and NRMSE, with the 6 models with different data types for the first study are presented in Table I. There is a slight reduction in the R^2 test every time the training data size is reduced. However, all the R^2 test values are over 0.90 which indicates that a small training size can be used while maintaining high test accuracy. The best training data size is mainly depends on the application. If the application's priority is fast processing with a good accuracy, then a small training data size should be used. However, if the priority of the application is the accuracy with a more general model, then a large training set should be used. Figure 4 shows a slightly decrease in the test accuracy when reducing the training data size. To the

TABLE I. R^2 TEST FOR THREE DATA TYPES AND DIFFERENT TRAINING DATA SIZE.

Metrics	Data type	Pronation-supination	Flexion-extension	Radial-ulnar
60% training size.	R^2 test	0.95	0.97	0.95
	NRMSE	6.4 %	4.9 %	7.03 %
50% training size.	R^2 test	0.94	0.97	0.94
	NRMSE	7.05 %	5.3 %	7.9 %
40% training size.	R^2 test	0.94	0.97	0.93
	NRMSE	7.2 %	5.3 %	7.9 %
30% training size	R^2 test	0.93	0.97	0.93
	NRMSE	7.3 %	5.3 %	7.9 %
20% training size.	R^2 test	0.92	0.96	0.93
	NRMSE	7.9 %	6.05 %	8.2 %
10% training size.	R^2 test	0.91	0.95	0.91
	NRMSE	8.3 %	6.2 %	9.5 %

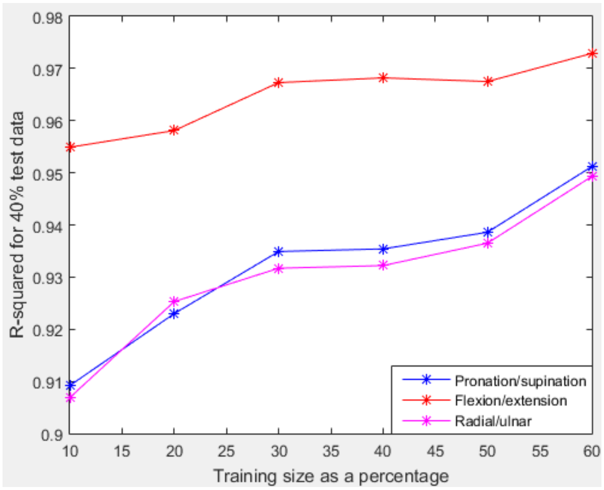

Fig. 4. R squared test with different training data size

TABLE II. AVERAGE R^2 TEST AND THE STANDARD DEVIATION FOR THREE REPETIONS FOR DIFFERENT DATA TYPES

Metrics / Data type	Avrg R^2	Standard deviation
Pronation- supination	0.92	0.012
Flexion-extension	0.93	0.036
Radial-ulnar	0.89	0.015

best of our knowledge, the results are unprecedented. Given the over 90% accuracy of the three models, it can be seen that the relationship between the FMG pattern and the models performance is consistent among different data collecting sessions.

V. CONCLUSION AND FUTURE WORK

In this paper, the viability of using an FMG based armband for predicting the isometric wrist/forearm torque is explored. The FMG based wearable device consisted of 16 FSRs sensors. Experiments are carried out using a Support Vector Regression with a radial basis kernel. Three regression models with different training data size are used to predict the torque values for the three different wrist/forearm deviations. These models achieve a promising accuracy (over 90%).

Future work aims at improving the results by adding some new features, using other machine learning methods, and testing the device with several volunteers.

VI. ACKNOWLEDGMENT

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