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On the estimation of isometric wrist/forearm torque about three axes using Force Myography

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Abstract— **Much of the morbidity and disability associated with industrial work settings arise from accidents involving humans and robots. Force Myography (FMG) is a potential technique to be used as an additional control measure for safer human-robot interaction without the need for robot hardware modification or replacement. The FMG signals represent the volumetric changes in the forearm due to muscle contraction, which were acquired using a Force Sensitive Resistor strap. A 1DOF torque sensor was used to model the point of interaction between a robot and a human. The following isolated upper extremity movements were considered: forearm pronation-supination, wrist flexion-extension and wrist radial-ulnar deviation. Torque regression models based on FMG data were created with two machine learning methods: Support Vector Machine (SVM) and Artificial Neural Network (ANN). Performance indices were defined and used for the comparative study between the two learning methods. The results demonstrated the feasibility of using FMG to estimate torque with accuracies around 90%. Both methods also demonstrated strong intra- and inter- participant consistency of FMG signals. The results will be beneficial for measuring the contact force between human and robot during their interaction.**

Keywords— Force Myography; Human Robot Interaction; Regression; Wearable Sensors; SVM; ANN;

I. Introduction

Applied research has shown that efficiency, flexibility, and quality in automated manufacturing plants, such as automotive assembly lines, can be highly improved through close cooperation between workers and robotic manipulators [1]. As a consequence, the past decade has seen a growing interest in bringing humans and robots closer together in the manufacturing environment [2, 3]. World-leading automation corporations, such as ABB, KUKA and Reis Robotics, have been developing robotic systems to cooperate with workers, without using separating safeguards, to maximize cooperation and throughput [4, 5].

While this economically-driven need has fostered the development of cooperative manipulators, accidents in the work place do still represent a serious concern that has highly hampered the introduction of collaborative robots. In fact, workers operating and maintaining automated machinery are at risk of serious injuries. US statistics suggest that 18,000 amputations and over 800 fatalities in the United States each year are attributable to such causes [6]. The most common cause of work-related injury is exposure to inanimate mechanical forces, which accounts for 46% of work related hospitalizations. The most common bodily location being injured is the wrist or hand (38%). Furthermore, 4.9% of wrist and hand injuries involve amputations [7]. A study performed in the US confirms that injuries to the hand and wrist are particularly high in automotive plants, especially in foundries and assembly plants [8].

The ultimate goal of the research in this area is to reduce the chances of injury where human workers and robots interact in automotive manufacturing facilities. During these worker-robot interactions, the angle and distance between the robotic arms and worker bodies is continuously changing [9] which make it a challenge to measure that distance. Several techniques exist for human detection and estimation of the relative locations so that collisions can be avoided [10].

First, to prevent collisions between humans and uncaged robots, a vision system is used to detect humans around the work space of a robot. Once a human is detected, a default sequence of robot control commands is executed to ensure worker safety [11, 12, 13]. Commonly, a fixed distance around the robot is assumed to be the safeguard zone. While cameras can be used for this purpose, they are still bulky and require high computational resources, which therefore prevent using them as wearable sensors in this application. Another practical limitation is worker privacy issues which can be a concern when cameras are used. Cameras also have a limited field of view even if they are mounted at relatively close distances (i.e. few meters) from the area of interest [14].

An alternative technique for detection of humans is using ultrasonic transmitters and receivers. Industrial operations such as impact, bending, grinding and drilling, and fluid or air sprays produce a significant amount of ultrasound noise; ultrasonic detection therefore requires operation at relatively high frequencies [15]. Ultrasound transceivers are usually directional and should be arranged into an array to obtain a reliable image of the surroundings [16]. Even though humans are relatively large targets, the amount of ultrasound reflections from them is quite small because humans are soft targets that absorb the majority of ultrasonic energy. Because of the aforementioned shortcomings, the use of ultrasound transceivers is challenging and often requires a significant amount of signal processing.

The third technique mainly aims at detecting collisions of the hand with moving objects. Therefore, both position and

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applied force of the hand should be monitored. A data-glove, such as the Cyber glove [17] which incorporates both inertial measurement units (IMUs) and flexible bend sensors, could be used to measure the position. However, data-gloves limit the tactile sensation of the user's fingers.

Furthermore, current active research focuses on processing bio-signals such as surface electromyography (sEMG) and electroencephalography (EEG) as controller inputs for robots, prosthetic devices and exoskeletons [18, 19, 20] also for predicting both hand posture and force [21, 22, 23, 24]. Even though this method frees the hand and allows full tactile sensation, it requires expensive and sizable equipment which also needs computationally expensive signal processing for detecting hand position and force.

Towards a safer human-robot interaction system, the objective of this work is to establish the feasibility of determining the magnitude of the torque in three directions using the FMG signals. Since it is inexpensive, lightweight and esthetically unobtrusive. The intention is that the FMG signals can be used as a part of a larger robot control system to monitor the force interactions during human robot cooperation. The rest of this paper is organized as follows: Section II describes the tools used in the experiment; Section III highlights the procedure of the data collection protocol; Section IV describes the data processing and the learning methods used; and Section V presents the quantitative findings and areas for further work. Conclusions are discussed in Section VI.

II. PROPOSED SYSTEM & EXPERIMENTAL SETUP

A. Force Sensing Resistor (FSR) Strap

A custom fabricated sensor strap composed of 16 force sensing resistors (FSRs) was used to detect the FMG signals related to the functional state of the participant's hand. The band length is about 38 cm, with a 1.7 cm distance between each two sensors in the band. With the help of Velcro tapes in both sides of the band, it can be fixed on the participant's forearm. The FSRs were incorporated into a voltage divider circuit. The base resistor in the voltage divider circuit controls the sensitivity of the FSRs. A Bluetooth module on the circuit control board was used to transmit the data from the strap to an on-site computer via custom LabVIEW software.

B. Mechanical Setup

Three custom-built rigs were designed to measure the isolated upper extremity movements: forearm pronation-supination, wrist flexion-extension and wrist radial-ulnar deviation. A Transducer Techniques torque sensor (TRT-100), was placed where its axis of rotation is aligned with the axis of rotation of the movement. The participant's forearm was secured to the rig using the Velcro tapes to restrict arm movement. The first setup was used to collect the wrist pronation and supination data. It consists of two aluminum plates with the torque sensor connecting them to each other as in Fig. 1. One of these plates is fixed to a table, while the other plate holds a handle that the participant holds on in order to exert isometric torque in the pronation-supination direction. The second setup was used to collect the wrist

Figure 1: The setup for collecting pronation - supination data.

flexion and extension deviations. As shown in Fig. 2, the setup is composed of two parts: a wooden base that holds the participant's forearm and two aluminum plates connected to each other through the same torque sensor, one of these plates holds the participant's hand. Fig.3 shows the forearm radial-ulnar data collection setup, which is mainly the same as the second setup except the torque sensor is placed under the participant's wrist to capture the radial-ulnar deviations.

The torque sensor in each setup was connected to an amplifier from Transducer Techniques (LCA-RTC) to adjust the sensor's output and increase the sensitivity of the sensor. The output of the amplifier is connected to data acquisition device (DAQ) from National Instruments (NI USB 6210).

C. Software

Custom LabVIEW software was used to collect both the applied torque and the FMG signals with a visual chart showing the exerted torque to guide the participant during the data collection session. This software established a Bluetooth connection with the band to acquire the FMG readings and simultaneously read the torque value with the DAQ. The data was acquired at a sampling frequency of 10 HZ. The collected data was then saved in a comma-separated values (CSV) file for offline processing and analysis.

A custom MATLAB® script was designed for processing the data, training and testing the regression model. The details of the data processing and regression model are described in Section IV.

III. EXPERIMENTAL PROTOCOL

An experimental protocol was designed to collect the FMG data and the exerted torque value to study the viability of using the FMG-based sensing system as a part of a robot controlling system. The previously defined setups were used to collect three degree of freedom data created with isolated upper extremity movements: forearm pronation-supination, wrist flexion-extension and wrist radial-ulnar.

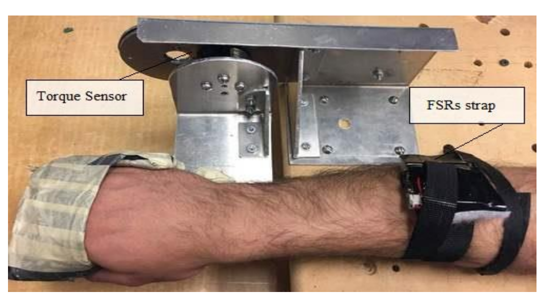

Figure 2: The setup for collecting flexion-extension data.

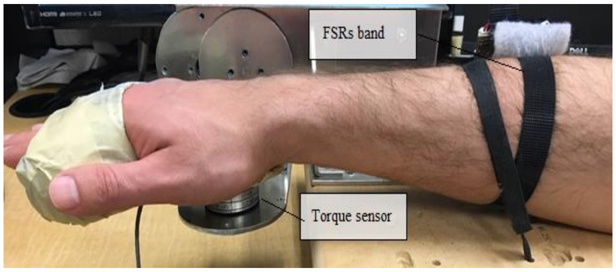

Figure 3: The setup for collecting radial - ulnar data.

Experimental data was collected from five healthy participants. Their average age was 25.2 years old and the average circumference of their forearm on the muscle belly, where the FSRs band was placed, was25 cm. The characteristics of the volunteers are detailed in Table I. Each volunteer provided written informed consent to participate, and this study was approved by the Department of Research Ethics of Simon Fraser University.

Three data collection sessions for each wrist/forearm deviations were carried out. Each session lasted for one minute to minimize the muscle fatigue. First, the band was tied on the muscle belly of the right forearm of each participant with the help of Velcro tapes. Then, they rested their hands on the defined place of the custom rig. After that, the participant alternated pronating and supinating the forearm to form an approximate sinusoidal wave, for one minute. The previously described procedure was repeated for the data collection of wrist flexion-extension and wrist radial-ulnar deviations, for three sessions. In every data collection session, there was a visual chart on LabVIEW that displays the exerted torque value with the result wave to visually guide the participant to maintain the sinusoidal wave form.

IV. Data Processing and Analysis

A. Data processing

Initially, the data from pronation-supination, flexion-extension, and radial-ulnar sessions were merged to be processed as a single dataset to predict multiple directions torque. The input in the combined data set is the FMG channels and the target is the torque values in three directions. For each sample in the data set, one out of three output columns has a value while the others are zeros e.g. if the first output has a value of 4 Nm, that means the input is

TABLE I. Participants' statistics.

	Gender	Age	Proximal forearm size (cm)
Volunteer 1	Male	30	25
Volunteer 2	Male	22	25
Volunteer 3	Male	25	26
Volunteer 4	Female	27	24
Volunteer 5	Female	22	25
Average	-------	**25.2**	**25**
STD	-------	**3.4**	**0.71**

the FMG signals corresponding to the pronation torque with a value of 4 Nm and the other two outputs are zeros that indicates the flexion-extension and radial-ulnar torques are zero. Through that data set, we can estimate the torque magnitude and direction across the three deviations data. A moving average filter with a window size equal to 3 is applied to each output to smooth the signals. After that, both of the FMG data and the three torque values were normalized to the maximum possible sensor value. Fig. 4 shows our proposed FMG signal processing scheme.

The FMG signals correspond to volumetric changes in the forearm that result from the relaxation/contraction of the forearm muscles during exerting force or torque [25]. The assumption behind FMG is that the generated force patterns, and thus volumetric changes, are distinct enough to discriminate between various wrist/hand/finger gestures and motions. The relation between the FMG signals and the exerted torque can be observed in Fig.5 where the FMG signals are centralized to the mean value. Two learning methods are used to capture this relation automatically, as there are different patterns of the FMG readings with the change of the torque direction.

B. Model production

The acquired data were analyzed for regression. All the machine learning methods that were used need to be first trained on a portion of the collected data where the target (the torque values) are known; this portion of data called the

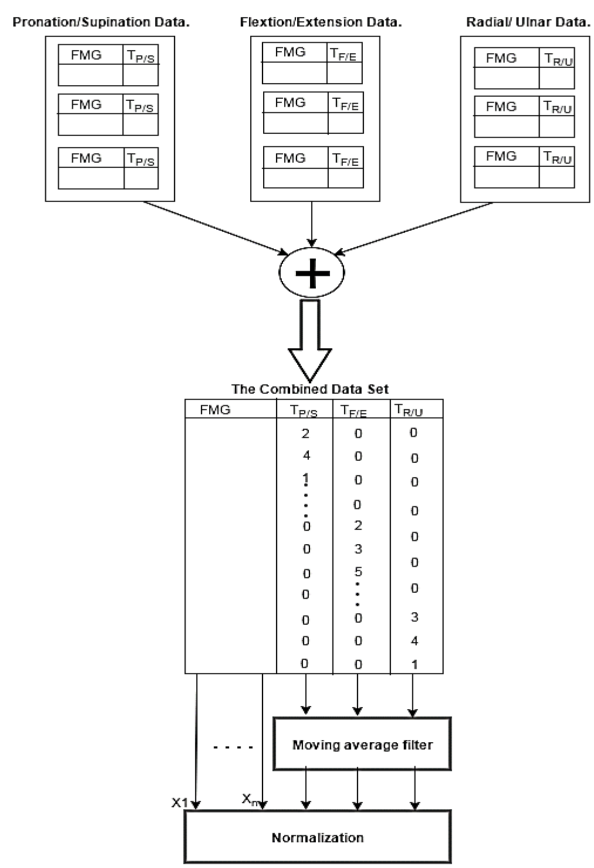

Figure 4: Signal processing scheme.

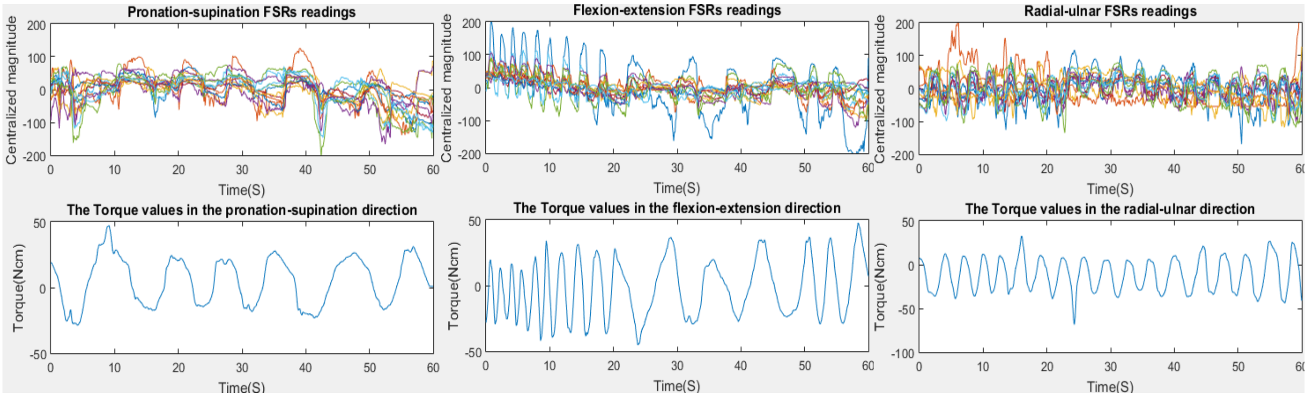

Figure 5: Example of the FSRs readings and the torque value in three different directions.

training set. Then, in order to assess the obtained models, they are tested on a separate set of data, called the testing set. In the experiments, the data was divided into 60% as the training set and the rest as the testing set.

The input space to the machine learning models is variable that is based on the volunteer's wrist size that in turn determines the number of usable sensors. The average number of the input data is 13 sensors readings out of sixteen sensors in the FSR band.

1. *Support Vector Regression (SVR)*

Support Vector Regression (SVR) is one of the Support Vector Machine (SVM) techniques which used for handling regression problems. SVR maps the input data to a higher-dimensional feature space where the data can be separated using the linear regression [26, 27].

The LIBSVM library [28] in the MATLAB® environment was used for offline processing of the collected data. Nu Support Vector Regression (υ-SVR) was used, as the υ parameter used to control the number of support vectors in the resulting model. We used the Radial Basis Function (RBF) kernel as it enables nonlinear mapping for the input data. Besides it has a small number of hyper parameters, which reduces model selection complexity [29]. 10-fold cross validation and grid search are used to find the optimal values for the model parameters (cost and gamma) [30].

2. *Artificial Neural Network (ANN)*

Artificial Neural Networks (ANN) are probably the most popular machine learning algorithm used for both regression and classification [31]. In the experiment, a two-layer feed-forward network with 100 sigmoid hidden neurons and three linear output neurons was used. Levenberg-Marquardt training was also used since it is much faster [32]. The number of the hidden nodes was determined empirically. Network structure is represented in Fig. 6, where n is the number of the processed FMG channels used as inputs to the ANN, $T_{P\text{-}S}$, $T_{F/E}$, and $T_{R/U}$ are the estimated torque values in the pronation-supination, flexion-extension, and radial-ulnar directions, respectively.

MATLAB® Neural Network toolbox [33] was used for training and testing the ANN models. To overcome the local minima problem, the training phase, for each model, was repeated ten times and the best model was chosen from those repetitions [34]. Also, early stopping and regularization were used to improve the generalization and reduce the likelihood of overfitting [33].

C. *Analysis*

Two experiments using both of SVR and ANN are carried out to compare between them. The first one was motivated by exploring the consistency of the FMG signals across different data collection sessions in three directions. 10-fold cross validation for the whole data is carried out and the standard deviation of the test accuracy across the ten repetitions was calculated.

The second experiment aims at exploring the ability of the FMG signal to estimate the torque values in three directions. The data was divided into 60% for training and 40% for testing. The SVM and ANN models were trained using the training data. Then, the result models were used to predict the torque values from the FMG signals in the testing data. The testing accuracy can be considered as a measure for the generalization ability of the resulting models.

V. Experimental Results and Discussions

The performance of the resulting models was measured by comparing the estimated torque values in three directions with the actual torque values in the testing set. Two accuracy metrics were chosen to compare the performance of different models: the coefficient of determination (R^2) and the normalized root mean square error (NRMSE) [35]. R^2 is a number that indicates how well the model fits the data, R^2 of 1 indicates that the model perfectly fit the data and R^2 of 0 represents that the model doesn't fit the data. NRMSE is a

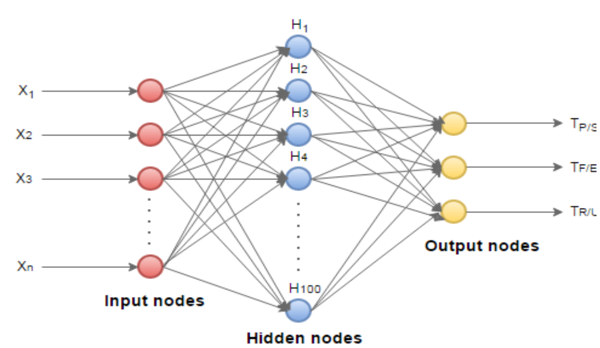

Figure 6: ANN structure

dimensionless metric which is a measure of the error percentage between the estimated and the actual torque values over the range of the actual torque vales.

First, the test performance of 10-fold cross validation using SVR and ANN, is presented to study the consistency of the FMG signals across the ten repetitions as in each repetition, a different portion of the data was chosen for the testing. Table II shows the average R^2 and the standard deviation from the ten repetitions for the five volunteers. The high accuracy (around 90%) and low standard deviation (around 0.02) seen in the 10-fold cross validation with two learning methods, suggest that the calculated torque models using FMG signals are consistent within a participant and across participants.

For the second experiment, Table III depicts the test performance metrics for each volunteer using SVR and ANN, respectively. The system achieves an average accuracy of 89% (STD = 0.03) across all the isometric deviations using the RBF-SVR. In addition, it achieves a comparable accuracy of 87% (STD = 0.02) across all torque directions using ANN. These results affirm the applicability of using the FMG signals for estimating the value of the isometric torque in three directions within different data collection sessions. The relation between the FMG and the exerted torque is captured very well regardless the change in the FMG pattern across different torque directions. Based on the scope of the experiment, SVM gives a better performance than ANN [36].

Another analysis has been done to explore the use of the FMG signals in predicting the torque direction. This study includes training the SVR model using the data of a torque direction and test that model using the data of another torque direction for example, the model trained using pronation-supination data and test that model using flexion-extension data. Theoretically, the predicted value from the model should be zero as the test set is a different torque direction data. The preliminary results show an average accuracy across the three models for the five volunteers is 0.008±0.001. It is not possible to make a concrete conclusion based on that result as the torque data in different directions should be collected simultaneously with the same placement of the FSR band which will be explored in the future.

TABLE II. AVERAGE R^2 FROM 10-FOLD CROSS VALIDATION USING SVR AND ANN.

ID	Metrics	**R^2 pronation - supination**		**R^2 flexion - extension**		**R^2 radial - ulnar**	
		SVM	***ANN***	***SVM***	***ANN***	***SVM***	***ANN***
P1	Mean	0.92	0.91	0.87	0.87	0.90	0.89
	STD	0.01	0.008	0.02	0.02	0.01	0.02
P2	Mean	0.93	0.91	0.86	0.85	0.95	0.95
	STD	0.02	0.01	0.04	0.01	0.007	0.003
P3	Mean	0.97	0.93	0.95	0.93	0.92	0.89
	STD	0.004	0.006	0.01	0.01	0.02	0.01
P4	Mean	0.92	0.91	0.95	0.92	0.92	0.92
	STD	0.008	0.01	0.02	0.01	0.02	0.008
P5	Mean	0.90	0.90	0.81	0.85	0.91	0.88
	STD	0.03	0.01	0.03	0.03	0.04	0.01
All	**Mean**	**0.93**	**0.91**	**0.89**	**0.88**	**0.92**	**0.91**
	STD	**0.03**	**0.01**	**0.06**	**0.04**	**0.02**	**0.03**

VI. CONCLUSION

This paper explored the viability of using an FMG based sensing system for estimating the isometric torque for the combined data of forearm pronation-supination, wrist flexion-extension and wrist radial-ulnar. The data acquisition system for the FMG and torque values was introduced. The system achieved promising average accuracy from 10-fold cross validation and low standard deviation within and across the participants in the three directions which prove the consistency of the FMG signals. Additionally, another experiment was carried out through training the model with a 60% of the data and evaluating the result using 40% of the data as a measure for its generalization ability. The system reached an average accuracy of 89% and 87% using SVR and ANN, respectively. These results affirm the potential practical viability of using an FMG based sensing system in estimating the torque value in three directions which in turn can be used in detecting the contact force during human

TABLE III. SVM AND ANN TEST PERFORMANCE METRICS.

	Pronation - supination				***Flexion - extension***				***Radial - ulnar***			
	SVM		***ANN***		***SVM***		***ANN***		***SVM***		***ANN***	
	R^2	***NRMSE***	***R^2***	***NRMSE***	***R^2***	***NRMSE***	***R^2***	***NRMSE***	***R^2***	***NRMSE***	***R^2***	***NRMSE***
Participant 1	0.91	0.03	0.87	0.04	0.83	0.06	0.82	0.07	0.86	0.05	0.85	0.05
Participant 2	0.90	0.04	0.84	0.05	0.83	0.07	0.80	0.06	0.92	0.04	0.94	0.03
Participant 3	0.96	0.03	0.91	0.04	0.93	0.03	0.90	0.05	0.90	0.04	0.86	0.05
Participant 4	0.92	0.04	0.89	0.04	0.90	0.05	0.89	0.07	0.90	0.04	0.89	0.06
Participant 5	0.89	0.06	0.87	0.04	0.81	0.07	0.81	0.07	0.88	0.05	0.84	0.06
Mean	**0.92**	**0.04**	**0.88**	**0.04**	**0.86**	**0.06**	**0.84**	**0.06**	**0.89**	**0.04**	**0.88**	**0.05**
STD	**0.03**	**0.01**	**0.03**	**0.004**	**0.05**	**0.02**	**0.05**	**0.009**	**0.02**	**0.005**	**0.04**	**0.01**

robot interaction.

VII. Acknowledgment

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