Estimating Force Exerted by the Fingers Based on Forearm Ultrasound

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***Abstract*—Biosignal-based finger force estimation is an active area of research, with applications in teleoperation, human-machine interaction, and rehabilitation robotics. Traditionally, surface electromyography has been used to estimate hand grip and finger forces. In this paper, we show that forearm ultrasound can be used to estimate the force exerted by the fingers. A wireless ultrasound probe strapped to the forearm and a force sensor was used to estimate the ground truth. Accuracy percentages and root mean square error (RMSE) values were obtained for the shuffled and non-shuffled data subjected to a test-train split for all the fingers. It was found that the classification accuracy was 98.4 percent for the shuffled data, and 82 percent for the non-shuffled data averaged over all the fingers. For continuous estimation, the average RMSE was 0.02 N for the shuffled data and 0.2 N for the non-shuffled data. With a maximum force of 5 N, the average RMSE accounted for 4 percent of the maximum force for the non-shuffled data, and 0.4 percent for the shuffled data. These results show the potential of utilizing forearm ultrasound for estimating finger forces.**

***Index Terms*—Forearm ultrasound, sonomyography, force, robotics, teleoperation, human-machine interfacing**

I. Introduction

For effective human-machine interfacing, intuitiveness and comprehensive tracking of hand dynamics is pivotal. This is particularly true for estimating finger movements and exerted forces. Biosignal-based hand movement and force estimation is an ongoing area of research and finds several applications in robot teleoperation, human-machine interaction, and rehabilitation robotics. Typically, surface electromyography (sEMG) has been used for estimating forces based on the electric signals coming from the brain to the hand through the forearm muscles [1]. However, there are issues surrounding the sensor signal-to-noise ratio, number of sensors required to get good data, etc. [2]. Ultrasound data from the forearm has been a useful modality for estimating hand movements and isometric force because it provides a visualization of a cross-section of the forearm. Previous works have shown ultrasound being used to measure finger movements [3], [4]. Using forearm ultrasound to measure isometric grasp force has also been demonstrated [5].

Merely isometric grasp force estimation is not sufficient, and it's important to get finer force measurement per finger to get force feedback for effective human-machine interfacing. Ultrasound data from the forearm gives us rich information about muscle morphology changes based on the force applied by each finger. These changes can be used to train machine learning models to estimate forces. The goal of this work is to estimate the force applied by different fingers. Two types of estimations are done: a) Binary classification between application of force and no application of force, and b) Continuous estimation of the force for different fingers. Machine Learning models are trained for different fingers for these estimations and the results are presented using accuracy percentage for classification and root mean square error (RMSE) for continuous estimation. The successive sections describe the methods employed and the results obtained for the study.

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II. Methods

After the ultrasound data and the corresponding ground truth are acquired, the data is processed and machine learning models are trained to estimate their performance to estimate forces using forearm ultrasound images. The overall workflow and different system components are depicted in figure 1.

A. System components

Ultrasound data was acquired using a Sonoque wireless linear ultrasound probe which was encased in a custom-designed wearable armband. The data from the probe was continuously streamed onto a computer screen, and this data along with the corresponding ground truth was acquired using a custom-designed Python script. A FlexiForce force sensor was used to acquire the finger force data. An Arduino was used to interface the force sensor to the data acquisition pipeline set on a Desktop. This sensor was calibrated using weights ranging from 10 grams to 500 grams. A quadratic fit function was used to calibrate the sensor. This is defined in equation 1.

$$weight = a * reading^2 + b * reading \quad (1)$$

where, $weight$ is the weight in Newtons (N), and $reading$ is the raw data acquired from the sensor. The values of a and b were found experimentally to be $1e^{-5}$ and $2.5e^{-5}$ respectively. The final function is shown in 2.

$$weight = 1e^{-5} * reading^2 + 2.5e^{-5} * reading \quad (2)$$

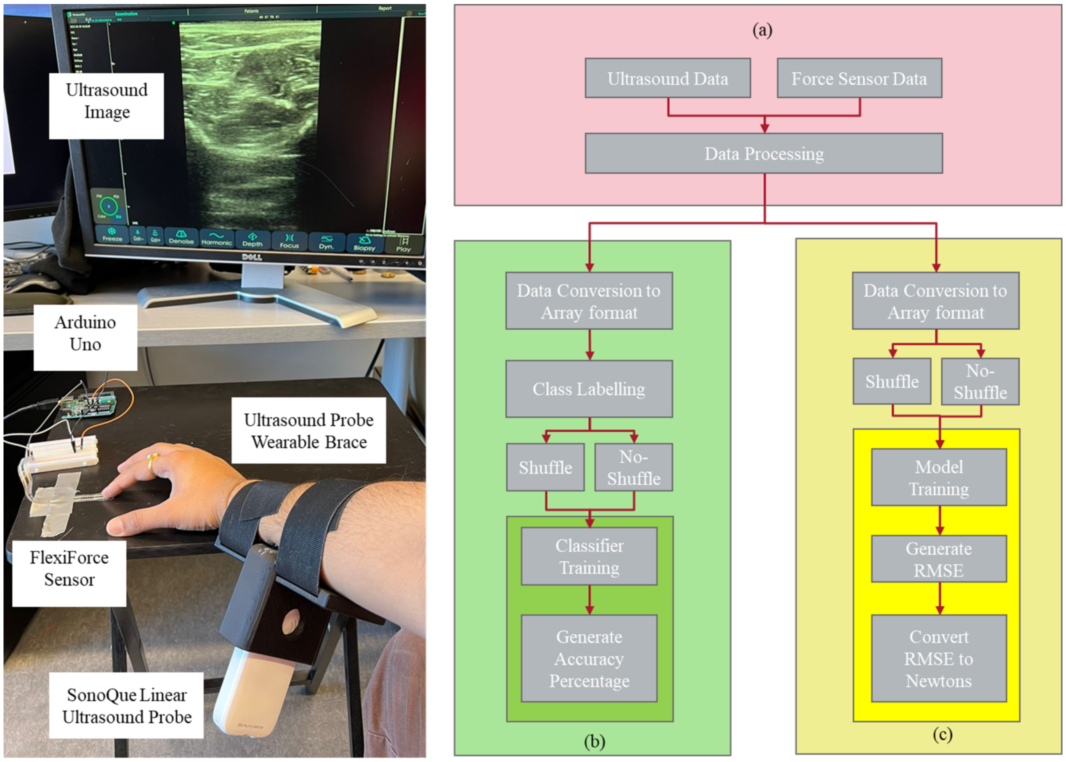

Fig. 1. System components and workflow: (a) The data acquisition block, (b) The classification block, (c) The continuous estimation block.

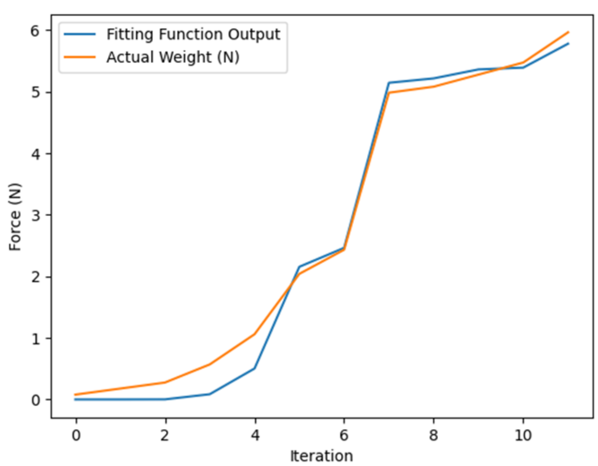

Fig. 2. Force sensor calibration using a quadratic fit function

The calibration curve is shown in figure 2.

B. Data acquisition

1000 ultrasound frames and the corresponding force data were acquired for each finger. The streamed data was saved at a frame rate of ∼4 Hz. The ultrasound image size was 640 x 640 pixels. The data acquisition was run three times. For classification, forces below 0.25 N were class 0, and the rest were class 1. The data was split into training and testing sets before and after shuffling with a split of 20%. The introduction of shuffled and non-shuffled datasets aimed to discern the impact of temporal dynamics on force estimation efficacy. Specifically, the shuffled dataset encompassed training and testing sets with temporal dependencies, while the non-shuffled counterpart featured temporally independent training and testing sets.

C. Model and metrics

A linear support vector classifier was used. It was a deliberate choice, given its established utility in prior research for hand gesture classification based on forearm ultrasound data [6]. Classification accuracy served as the benchmark for evaluating classification performance, while continuous force estimation was evaluated using the root mean square error (RMSE). The classification accuracy percentage is defined in equation 3.

$$Acc = \frac{CC}{TC} * 100 \tag{3}$$

where, Acc is the classification accuracy percentage, CC is the number of correct classifications and TC is the number of total classifications. The RMSE is defined in equation 4.

$$Err = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} \tag{4}$$

where, Err is the root mean square error, x_i is the actual value and $\hat{x}_i$ is the predicted value of the ith observation. N is the total number of observations.

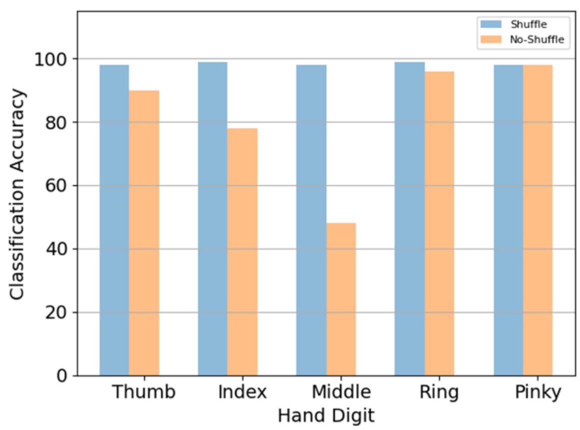

Fig. 3. Classification accuracy for the hand digits

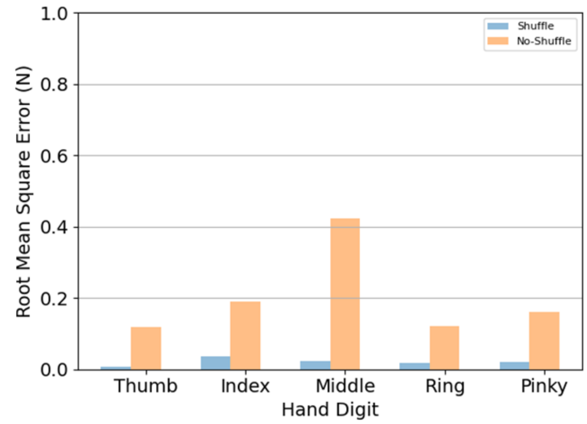

Fig. 4. Root mean square error for the hand digits

III. Results

The results for binary force classification and continuous estimation of force for different fingers are described in this section.

A. *Classification accuracy*

Accuracy percentage values were obtained for the shuffled and no-shuffled cases for all the fingers. It was found that the average classification accuracy was 98.4 ± 0.5% for the shuffled case, 82 ± 20.54% for the non-shuffled case. The classification accuracy results are shown in figure 3. Shuffled data in general had a higher performance than non-shuffled data. The standard deviation for non-shuffled data was higher. This divergence could be attributed to the temporal dependencies present in the training and testing sets of the shuffled data. Notably, the accuracy percentage for the non-shuffled scenario remained within a 25% range of the shuffled counterpart, except for the middle finger classification, which fell below 50% of the shuffled accuracy. Future work will be directed toward enhancing the accuracy of non-shuffled results, particularly for both index and middle fingers.

B. *RMSE for continuous estimation*

For continuous estimation, averaging the results over all the fingers and considering the maximum applied force of 5 N, the average RMSE was 0.02 ± 0.01 N for shuffled data and 0.20 ± 0.13 N for non-shuffled data. The RMSE values for each finger are shown in figure 4. As was observed for classification, time dependence in the test and train sets for the shuffled data leads to lesser error compared to the non-shuffled set. For the non-shuffled set, just like it was observed for classification, continuous force estimation for the middle finger performed the worst with a RMSE value greater than 0.4 N. For the worst case based on the standard deviation, for the shuffled data, the error was 0.03 N which is 0.6 % of the maximum value. For the non-shuffle data, this was 0.33 N which is 6.6 % of the maximum value. These results are encouraging, and future work will focus on improving the no-shuffle time-independent analysis results using deep learning algorithms.

IV. Conclusions

In conclusion, this study demonstrates the use of forearm ultrasound for estimating both binary and continuous finger forces. A wearable ultrasound probe and a force sensor were used to acquire data. Using a linear support vector classifier, an average classification accuracy of 98.4% for shuffled data and 82% for non-shuffled data was obtained, For continuous estimation, an average RMSE value of 0.02 N for shuffled data and 0.2 N for non-shuffled data were obtained. These findings offer encouraging prospects for future research for using forearm ultrasound for finger force estimation. The non-invasive and data-intensive nature of ultrasound makes it a sensor of choice for human-machine interfacing, and this study contributes to the gradual advancement of biosignal-based non-invasive finger force estimation methods and their potential applications.

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