Hand-Grip Strength Estimation through Bioacoustic Sensing

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***Abstract*—In order to determine the overall health of an individual, hand grip strength has emerged as a reliable and widely used indicator of muscular and functional health. However, the conventional devices for measuring grip strength, such as dynamometers, require direct interaction with a bulky external device. In this work, we propose a novel, cost-effective approach to estimate grip strength using bio-acoustic signals captured from the forearm via a compact armband equipped with low-power MEMS microphones. Our method performs well on grip strength classification with an accuracy of 93.33%, and as a proof of concept, demonstrates a promising direction for non-invasive grip strength estimation.**

***Index Terms*—grip strength estimation, bioacoustic sensing**

I. Introduction

In recent years, hand grip strength (HGS) has emerged as an important biomarker of health, where lower values are associated with an increased risk of cardiovascular diseases, type-2 diabetes, kidney and liver issues, stroke, sarcopenia and osteoporotic fractures [1]. Prior studies also suggest that lower HGS is linked to a higher risk of developing psychosomatic disorders, mainly depression and anxiety [3]. In addition to its strong correlation with the onset of various diseases, HGS is also widely used among athletes, mainly in sports where gripping and controlled force application is critical, such as golf, hockey, rock climbing, weightlifting, racket sports, to improve performance and reduce the risk of injury [2].

Among the methods commonly used to estimate hand grip strength (HGS), most involve interaction with an external sensing device. The dynamometer, the most widely used tool for measuring grip strength, requires individuals to exert force on its handle, converting this mechanical pressure into a readable force value displayed in kilograms or pounds. The Jamar hydraulic dynamometer, widely considered the gold standard for measuring HGS, is most commonly used in clinical assessments. Other types, such as pneumatic and strain gauge dynamometers, are used in specific contexts [4], while mechanical (spring-type) dynamometers with digital displays are commonly employed in general settings. However, these devices need precise positioning, frequent calibration, and can give unreliable readings if used incorrectly, making them impractical for routine or long-term use. To address these limitations, some recent works have explored wearable devices to estimate grip strength, trying to offer a compact and user-friendly alternative to traditional dynamometers. These include glove-based or ring-based designs that use force-sensitive resistors (FSRs) [5], light sensors [6] or capacitive force sensors [8]. The existing works using surface EMG sensors [9]–[11] typically attach the EMG patches at specific locations on the forearm to measure grip strength. On the other hand, wristband or armband designs aim to estimate grip strength indirectly by capturing muscle activity or skin deformation, offering a more general and less intrusive solution. Wang et al. [7] introduced a flexible deformation sensor for measuring the grip strength. However, the glove/ring-based methods are constrained by user-specific customized design, surface EMG depends on skin characteristics, and deformable sensor-based approaches face material durability concerns, which together pose challenges for long-term use.

In our work, we explore the feasibility of estimating grip strength leveraging bioacoustic signals at the forearm by mounting MEMS microphones on the muscle belly near the elbow to capture vibrations from muscle activity. The forearm muscles primarily consist of extrinsic and intrinsic muscles. Extrinsic muscles, which originate in the forearm, are the main contributors to grip strength. Intrinsic muscles, on the other hand, originate within the wrist and hand and are important for precision and coordination, but do not significantly contribute to grip strength.

The key contributions of our work are summarized as follows:

- We propose a novel method to estimate hand grip strength through passive sensing of bioacoustic signals generated by muscle activity during gripping using MEMS microphones.
- Our wearable device consists of a self-contained armband that is comfortable to wear, offers a snug fit, and maintains performance regardless of occlusion or varying skin characteristics.
- We design compact, cost-effective, and low-power sensors to effectively capture muscle vibrations as acoustic signals on the skin surface.

II. Methodology

A. Anatomical Considerations for Sensor Mounting

Previous studies have primarily focused on sensing muscle activity using EMG methods [10], targeting two major muscles on the radial side of the forearm: flexor carpi radialis

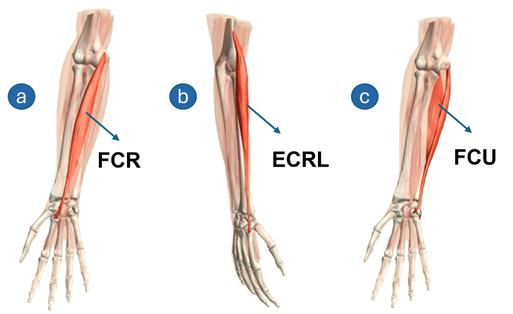

Fig. 1. Illustration of forearm muscles involved in hand gripping, depicting (a) FCR (b) ECRL (c) FCU muscles.

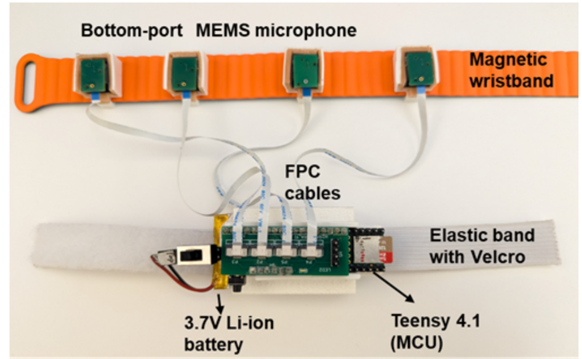

Fig. 2. Wristband design involving MEMS sensor enclosed within the sensor mount along with MCU and battery unit.

(FCR) and extensor carpi radialis longus (ECRL), to determine optimal sensor placement. These muscles contribute to grip strength by stabilizing the wrist through coordinated flexion and extension, which enhances the efficiency of the finger flexors. In addition to these, we also consider the flexor carpi ulnaris (FCU), a superficial and robust muscle on the ulnar side that plays a key role in wrist stabilization during gripping. To capture vibration signals, we mount two MEMS sensors near FCR and ECRL, and two more around FCU.

B. Hardware

The main sensing element consists of MEMS microphone ICS-43434, a bottom-port microphone with a form factor of $3.5 \times 2.65 \times 0.98$ mm ($L \times W \times H$). These microphones are housed within 3D-printed shell consisting of foam layers in-between, designed to enhance the robustness towards external noise. The four microphones are connected to the MCU (Teensy 4.1) through a connector board using FPC cables. The microphones along with the shell are attached to a magnetic wristband, where the position and placement of the microphones can be adjusted based on the user arm width. The MCU and the battery are enclosed in a 3D-printed casing which is attached to an elastic band that can be secured with Velcro. Although the armband design is currently not optimized for low power, the sensing system is inherently low power, with each MEMS microphone consuming around 1.17 mW in normal operational mode.

C. Signal Processing and Feature Extraction

The recorded audio signals from the armband are truncated or zero padded to obtain signals of equal lengths of 6 seconds. These signals are sampled at a sampling rate of 22050 Hz and are split into segments of 0.5 seconds. Spectrograms are computed for the individual segments, with the number of FFT set to 400 and a hop length of 160. The idea behind splitting the audio signals into segments is to get spectrograms of reasonable dimension, while also capturing the details within each segment. The obtained spectrograms are converted to decibel scale, and the spectrograms from all four microphones are stacked, creating a four-channel input to the deep learning model.

D. Model Architecture

We evaluate and compare the performance of three different model architectures using input audio spectrograms. The first architecture consists of a two-layer convolutional encoder applied to the spatial dimensions, followed by a single-layer LSTM operating on the temporal dimension. The resulting feature representation is concatenated with metadata and passed through fully connected layers to generate the final prediction. This particular model was trained for 100 epochs to achieve optimal results.

The second architecture retains the same overall structure, with the primary difference lying in how the metadata is integrated. Instead of direct concatenation, the metadata is first passed through an embedding layer, and the resulting representation is then concatenated with the output of the LSTM before being fed into the fully connected layers. This modification led to faster convergence, with the model stabilizing after approximately 30 epochs.

The third architecture employs a U-Net framework to process spatial dimensions, with skip connections between a compact two-block encoder-decoder to preserve fine-grained information. This is followed by a temporal modeling stage using an LSTM, whose output is concatenated with embedded metadata features. The combined representation is then used to generate the final predictions. For training the above-mentioned models, the Adam optimizer was used with a learning rate of 5×10^{-3}, and the L1 loss function was employed. All the models were trained on a personal laptop equipped with an NVIDIA GTX 1660 Ti GPU (6 GB memory).

III. Experiment

Experiments were conducted on 5 participants (3 male and 2 female), aged between 20-30, with 15 trials for each participant. These trials included weak and normal grip strengths depending on their age and gender. The participants were asked to sit comfortably on a chair, placing their arm on the armrest at a 90° angle at the elbow. This has been the standard way of measuring grip strength. The subjects are instructed to hold the dynamometer in their dominant hand, with the armband being attached to the forearm.

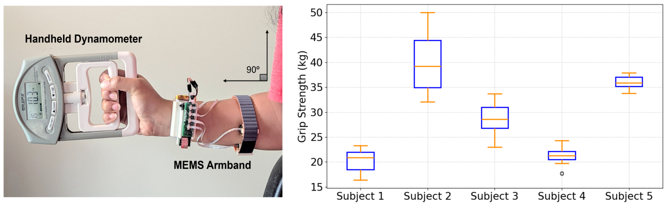

Fig. 3. Left: Data collection setup using the armband and dynamometer with the forearm positioned at a 90° elbow angle. Right: Variation in grip strength values across different participants.

To analyze the grip strength using data collected from multiple subjects, we use box plots to visualize the variability across individuals and identify patterns in muscle performance. This helps detect outliers and assess consistency within each subject. From Fig. 3, we observe that Subjects 2 and 5 exhibit stronger grip overall, while Subject 2 showing the highest variability and Subject 5 demonstrating consistent strength. Subjects 1 and 4 fall towards the lower end, with Subject 4 displaying a few outliers. This highlights the diversity of our subject pool in terms of both strength levels and variability, which is essential for developing models that generalize well across different populations.

IV. Results and Discussion

The hand dynamometer typically reports grip strength in kilograms or pounds, along with a discrete category indicating the level of grip classified as weak, normal, or strong. These categories are determined based on the subject's age and gender, which are essential for calibrating the device. Categorizing grip strength provides meaningful insight into whether an individual's strength falls within the expected range, rather than focusing solely on numerical values, which can be convenient for regular monitoring without having to check which category the measurement belongs to. In our study, all participants exhibited both weak and normal grip strength, at different times with approximately equal representation. To avoid class imbalance, we excluded data from one participant predominantly consisting of the weak class, leaving a dataset of 5 subjects. The dataset comprised training and testing data split in an 80-20 ratio, with a total of 75 trials. We evaluated two models: a two-layer LSTM model trained on audio spectrograms, and a CNN-LSTM hybrid model. The LSTM model achieved a classification accuracy of 73.33%, while the CNN-LSTM model reached 93.33%, with only one misclassification out of 15 trials. Both models were trained for 20 epochs using binary cross-entropy (BCE) loss.

For grip strength estimation, we assess the performance of different model architectures on the input audio data using regression metrics, root mean squared error (RMSE) and coefficient of determination R^2. RMSE measures the average prediction error, where lower values indicate more accurate estimates. R^2 indicates how much of the variation in the target variable is explained by the model, where higher values indicate a better fit. From Fig. 4 we can observe that Model 1 has the highest RMSE and lowest R^2 values (RMSE = 6.6894, R^2=0.3246), while Model 2 performs better than Model 1 with an RMSE of 5.938 and R^2 of 0.4678. However, we can notice that Model 3 has the lowest RMSE of 5.68 and highest R^2 of 0.5130. The overall range of grip strength values in the dataset spans approximately from 17 kg to 50 kg. Considering the large variation in the experimental measurements, the predicted RMSE of 5.68 kg from a model trained on the entire dataset reflects reasonable performance.

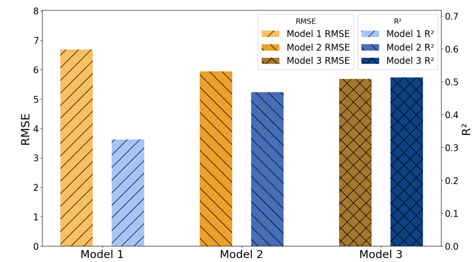

Fig. 4. Overall comparison of model performance using RMSE and R^2 metrics.

Fig. 5 shows the variation of RMSE among different subjects for each model architecture. Model 3 is the most robust, with consistently lower or comparable RMSE across all subjects. Model 1 on the other hand, lags behind, indicating weaker generalization.

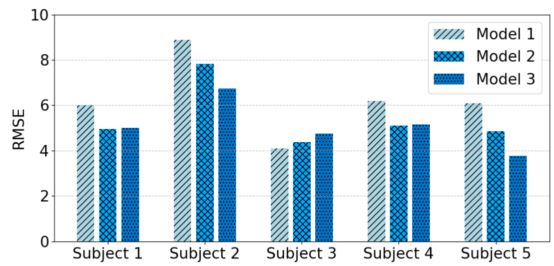

Fig. 5. Comparison of model performance across all subjects based on RMSE values.

To test the robustness of our armband-based system, which relies on acoustic sensing, we evaluated its performance under varied environmental conditions with different noise levels. This was done to assess how external acoustic interference impacts the predictions. In addition to the normal setting, we considered two indoor and outdoor scenarios. For indoor noise tests, we included background jazz saxophone music and ambient noise from a busy café. For the outdoor setting, we tested with noise from heavy rain and thunder, as well as traffic on a busy road. In all the cases, the subject was approximately 0.7 meters from the noise source, and the noise level was measured near the subject. Fig. 6 shows that the model output is unaffected by most noise conditions, with RMSE values comparable to the normal setting. We also tested the armband under the clothing and found that the performance does not degrade despite the occlusion.

TABLE I
DIFFERENT NOISE SOURCES CONSIDERED FOR ROBUSTNESS TESTS.

Environment	Noise source	Noise level (dB)
Indoor setting	Controlled environment	32.1
	Background music	60.8
	Busy café	65.1
Outdoor setting	Heavy rain with thunderstorm	62.5
	Busy road	70.6

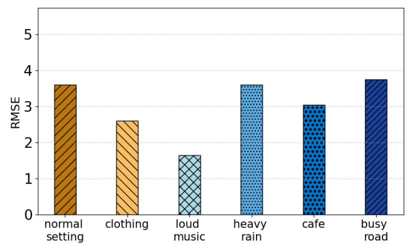

Fig. 6. Robustness evaluation of the system across different noise environments and with the armband worn under clothing.

V. RELATED WORKS

Bioacoustic sensing in humans has been applied across a wide range of medical and biometric contexts. Prior studies have investigated the possibility of noninvasive monitoring of various bodily functions through bioacoustic signals. Some of these include the detection of cardiovascular abnormalities or diseases, respiratory illnesses, sleep disorders by monitoring the tracheal sounds, and gastrointestinal disorders [12]. Additionally, bioacoustic signals have been leveraged to detect vocal disorders [13], assess swallowing difficulties (dysphagia) [14], and identify bone-related abnormalities by capturing the knee joint sounds [15]. More recently, multichannel acoustic spectroscopy has demonstrated the ability to capture distinct acoustic transmission patterns for each finger, enabling highly accurate biometric authentication based on the internal anatomical and material characteristics of the hand [16].

VI. CONCLUSION

In this work, we introduced a novel passive sensing approach for capturing bio-acoustic signals from forearm muscle activity to classify and estimate hand grip strength. The proposed armband is cost-effective, comfortable to wear, and incorporates small, low-power sensing elements. As a proof of concept, the prototype achieves a classification accuracy of 93.33% and demonstrates promising results for grip strength estimation. With further improvements, it has the potential to become a convenient and compact tool for monitoring hand grip strength.

Bioacoustic signals vary across individuals due to differences in muscle composition and may require a user-specific model fine-tuned on a small amount of data from each new user to achieve optimal performance. Although each MEMS microphone features a small form factor and low power consumption, the entire armband design can be further optimized to reduce size and the overall power usage. While our current study includes five subjects aged between 20-30, future work will involve expanding the participant pool to cover a broader age range, particularly focusing on older individuals.

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