



Design of a Wearable EMG–IMU Gesture Recognition System for Real-Time Sign Language Translation in Assistive Communication Applications

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ABSTRACT

Communication barriers have existed between the speech-and-hearing-impaired people and rest of the world due to the non-mainstream nature of sign language (SL). While there are proposed options to translate, most of them are costly and undeployable. The paper aims to create an affordable system to provide impaired users ability to communicate with normal people easily using text-to-speech (TTS) technology with the power of artificial intelligence (AI) and Internet of Things (IoT), powered by ESP32 to accurately predict SL. This is supported by dual channel electromyography (EMG) sensors and 6 axis gyrometer that is processed through filtering and feature extraction to give out high quality data for prediction. This system allows seamless communication enabled by MQTT and Wi-Fi connection from a wearable glove to collect required data that is used to train a Random Forest (RF) model. On a held-out validation set the system attained 92% accuracy; however, in on-field deployment this fell to about 53% (38–70% across the three gestures), so the system is presented as a feasibility prototype rather than a deployment-ready aid. As a starting point for this approach, future work will expand the dataset with more participants and gestures, complete a subject-independent evaluation, and refine the wearable device.

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1. INTRODUCTION

Communication is one of the most important aspects of a human's life. One of the means humans communicate with each other is through nonverbal actions such as body language. Usually, it complements the verbal communication process, giving it more context to what is being talked about. However, people with hearing and voice disabilities cannot use verbal communications and resorts only for nonverbal communications such as SL. One problem with this is that most people in the world do not understand SL and this creates a gap between them and the disabled, preventing them from connecting with the world and feeling left behind. Although there are studies being done to create automatic SL translators,

the implementation is still very limited and requires more study. In addition, advancements in electromyography provides a possibility of using it to read gestures, although the development are still in the early stages.

The work aims to create an EMG-based SL translator with the help of pattern recognition ability from Artificial Intelligence (AI) models that provide outputs in the format of a speech while still being wearable, portable and affordable. The work covers the area of IoT and AI by integrating a physical device that utilises EMG and inertial measurement unit (IMU) sensors to receive electrical input from the muscle movement of the user alongside the hand's acceleration and position. The

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data is then translated into SL and sent to the user via speech output.

Monetary issue is the main concern of the work since the work would need EMG sensors which could fetch a steep price. Another issue the feasibility of the work as there are no available datasets to train an AI model. The work needs to be clear on the fact that the lack of training data may lower the accuracy of the model. The process of training the data can be hindered by the difficulty of training the data itself, since EMG inputs are electric signals that can vary and contains noise.

This work hopes to provide those who have hearing disabilities a better means to communicate with other people around the world, making them heard and appreciated. The automatic SL translator does not require someone to be familiar with SL to understand it, lowering the barrier between the two. In addition, this system aims to bridge the gap between the deaf and the rest of the world so they can have as much knowledge of the world as a normal person would be.

As a disclosure, a preliminary version of this manuscript was presented virtually at the IGIIDEATION 2026. Relative to that preliminary version, this manuscript adds a complete on-field deployment with quantitative evaluation, an explicit disclosure of the data-splitting protocol together with a subject-independent (leave-one-subject-out) re-evaluation, a sensor-modality ablation study, an end-to-end latency characterisation, and a bill-of-materials cost analysis.

2. REVIEW OF PREVIOUS WORK

2.1 Overview of Related Studies

Several studies in the past have explored the idea of SL recognition using surface EMG (sEMG) using many types of devices, categorized into the ones already on the market and self-made experimental builds. Studies that belong to the first category mainly use Myo Armband [14, 22], BIOPAC MP36 system [6, 9] and Delsys wireless trigono sensors [16, 17]. Some other notable mentions of off-the-shelves systems used in some studies are G-force sensors [25], Myo thalamic bracelet [18] and MyoWare 2.0 sensor [15]. Something to keep in mind is that the Myo's thalamic bracelet and sensor are different from the more commonly used armband, which is a whole package of both EMG and IMU sensors. On the other hand, other studies prefer to make their own system that are able to collect sEMG data and optionally, IMU data [11, 19]. There are some key features or decision designs on these devices that are worth a mention. For example, reference [7] uses Arduino Uno as a basis for their system in order to control their 6 sEMG sensors. Reference [21] made the sensors from scratch using 7 stainless steel dry electrodes, integrated in self-designed circuit.

A common step in data pre-processing before AI model training is feature extraction. Some common extracted features from sEMG signals are mean absolute value (MAV), standard deviation, variance, skewness, zero crossing (ZC) and Willison Amplitude (WAMP) [17, 25]. This is due to the importance of having distinct features as it helps improving the system's performance. Other studies added more features from the list above such as root mean square (RMS), slope sign change (SSC), and waveform length (WL) [3, 8]. Reference [2] opts for a deeper feature extraction network using Convolutional Neural Network with Convolutional Block Attention Module

(CNN-CBAM). Reference [4] also took a similar approach via CNN layers with Long Short-Term Memory (LSTM) layers after. Reference [23] takes another approach via short Fourier transform (STFT) to gather spectral information from a spectrogram.

After pre-processing the sEMG data, it is then sent through trained ML models to predict SL gestures. Before continuing, it is important to point out that reference [5] does not use any ML models in their work. Generally, there are a few popular models used in past studies due to the performance it has towards sEMG datasets. The top ML models used are random forest (RF) [18, 21], LSTM [1, 23] and CNN with its subclasses [1, 22]. Moreover, combining CNN and LSTM is also a popular approach [2, 4]. Other common ML models are linear discriminant analysis (LDA) [9, 21], multilayer perceptron classifier (MLP) [14, 24], K-nearest neighbour (KNN) [14, 21], decision tree (DT) [3, 20], Naïve Bayes (NB) [14, 18], logistic regression [17, 18] and support vector machine (SVM) [13, 20]. However, unique models are also used for SL prediction that has never been done before. References [7, 10] uses gradient boosting algorithm such as Extreme Gradient Boosting Machine (XGBoost) and Catboost, respectively. On the other hand, Weka deep learning [13], hidden Markov model [16] and bilinear classification model [12, 24] also have been tested for SL recognition (SLR). Lastly, reference [25] goes for reinforcement learning techniques by using deep Q-network algorithm.

2.2 Discussion

When reviewing what type of EMG input device to be applied for the work, using an off the shelf device may be beneficial. However, while this can expedite the work as the data gathering process and ML model development can be done right away, these devices are expensive [4, 8] and is not made specifically for EMG data collection. The only exception is the MyoWare 2.0 Sensor, as it comes at a low price [15]. This led to some complications when trying to capture sEMG data. Reference [1] cited some struggles on trying to recognize hand shapes using Myo Armband. Moreover, Myo Armband's sampling rate of 200Hz is not enough to capture sEMG data, which are around 800 to 1000Hz [12]. The BIOPAC system, while providing good results, is an advanced system for professionals and thus not suitable for normal users [15]. The other option is designing a specific device for EMG data collection from scratch. This can help reducing the cost of the device and making it tailored towards the work's objectives. However, it will take time to design and test the device before it can be deemed ready to be released. If this approach is to be taken, there are some key things that can be learned from past works. For example, reference [7] concludes that Arduino Uno is a slow microcontroller and has big form factor, possibly hindering real-life application. In addition, usage of multiple sensors has shown to help improving performance of the system [2, 5].

In terms of the ML models, all ML models presented has managed to achieve more than 80% accuracy, showcasing good performance overall. However, there are some key details some models have after evaluations. First, reference [12] claims that their LSTM and bilinear model setups can provide SL translations with less than 50ms delay. In addition, the bilinear model is seemingly found to be able to eliminate individual differences between data. Reference [10] concluded that the Catboost algorithm can maintain good scalability without

sacrificing its performance. On the other hand, reference [13] added kappa statistics in their testing and found that RF and Weka deep learning model achieves 0.9987 kappa value, solidifying both models to be the best over the rest that are tested. Receiver operating characteristic (ROC) curve is also used for RF model, where it achieves 0.97 area under the curve (AUC), indicating an almost perfect classification model. Furthermore, many studies cited some more advantages of RF, such as good robustness and performing well on all tests [14]. In addition, RF is found to work better on less channel systems [18] and has low computing time without sacrificing accuracy [21]. However, one place RF is found struggling is when some gestures are like each other [3].

Based on this, the work will be adapting the approach of using a made-from-scratch wearable EMG input device as wearability and affordability are the main objectives for the device. The device will use multiple sensors alongside an IMU sensor while keeping it relatively wearable to the user. As such, a microcontroller will also be implemented into the device design. For the ML model, Random Forest is possibly the best approach for the work as it still can compete with the likes of CNN or LSTM but still able to provide close to real-time outputs. Another key thing learned from these studies are the importance of feature classification for a high performing model and as such must be part of the system design. In addition, any raw EMG data must go through a pre-processing module to clean it from noises. This allows for only values related to the sign gestures are collected and nothing else [6, 8]. Moreover, the data collection process must be done with supervision or collaboration with representatives of the deaf or mute people or at least those who are fluent with SLs to keep the recorded data accurate and valid [1, 4]. Lastly, segmentation should be applied during the data collection process for each gesture as it prevents the loss of important data [6].

3. METHODOLOGY

3.1 System and Hardware Design



Fig. 1. Sign Language Translator Device

The Motion-to-Speech Translators hardware consists of three key components; an ESP32 microcontroller, dual-channel surface EMG sensors and 6-axis IMU sensor. Components are combined into a single circuit with a power supply system to make a functional, wireless, and rechargeable device. A Printed Circuit Board hold those circuit, encased into a 3D-printed box, which is attached to an arm glove, to make a wearable device as shown is Fig. 1.

3.2 System Architecture Design

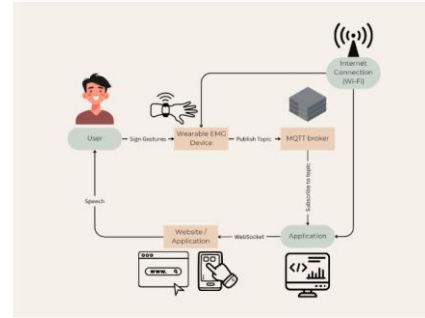


Fig. 2. System Architecture Design

As shown is Fig. 2, the ESP32 acquires the dual-channel EMG and IMU signals before being transmitted via MQTT over Wi-Fi to a processing application. The transmitted data include timestamped EMG and inertial measurements, which are processed for feature extraction and classification using the model. The predicted output is then sent to a web-based application for real-time display and speech synthesis.

3.3 Data Collection



Fig. 3. Sign Language Gestures

Training data is collected before training the model. 3 participants are required to complete three different American Sign Language gestures ("Thank you", "Help" and "Welcome") as shown in Fig. 3, each 30 times, resulting in a participant to contribute to 90 samples, 270 samples in sum. The three participants were healthy adult volunteers; none is a native or habitual user of sign language, and each was trained to reproduce the gestures in accordance with established American Sign Language standards prior to recording.

In the beginning of each sample recording, the participants are required to start in resting position. Each sample recording last for 4 seconds, and the participants are required to hold the position of the sign language until the 4 seconds is up.

3.3.1 Physical Setup



Fig. 4. Muscles for EMG Channels

Before data collection and device deployment, the dual-channel EMG sensors need to be connected to the participant's right forearm. Each channel is connected to the Brachioradialis in Fig. 4(a) and Flexor Digitorum Ulnaris in Fig. 4(b). These muscles are selected as they're involved in wrist and finger movements relevant to the gestures.

3.3.2 Feature Extraction

The samples are sliced into 500 milliseconds windows with 50% overlap, to get more samples out of existing ones, which results in 3009 windows samples. Features extraction method is done using these following features:

- Mean Absolute Value (MAV)

$$MAV = \frac{1}{N} \sum_{i=1}^N |x_i| \quad (1)$$

- Root Mean Square (RMS)

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (2)$$

- Zero Crossing (ZC)

$$ZC = \sum_{i=1}^{N-1} [sign(x_i) \neq sign(x_{i+1})] \quad (3)$$

- Waveform Length (WL)

$$WL = \sum_{i=1}^{N-1} [x_{i+1} - x_i] \quad (4)$$

- Variance (VAR)

$$VAR = \frac{1}{N-1} \sum_{i=1}^N [x_i - \bar{x}]^2 \quad (5)$$

- Integrated EMG (IEMG)

$$IEMG = \sum_{i=1}^N [x_i] \quad (6)$$

3.3.3 Selection of Machine Learning Model

Table 1. Model Comparative Analysis

Model	Accuracy	Precision	Recall	F1-Score	Training Time(s)	Inference Time(ms)
Random Forest	0.92	0.92	0.92	0.92	7.88	0.104
MLP	0.91	0.91	0.91	0.91	3.44	0
SVM	0.87	0.87	0.87	0.87	0.59	0.1
KNN	0.86	0.86	0.86	0.86	0.01	0.08
Decision Tree	0.85	0.85	0.85	0.85	0.08	0
Logistic Regression	0.80	0.79	0.80	0.80	0.07	0.02

A comparative analysis is done to evaluate models to be used for the system. Each model is trained using the same extracted features dataset in Section 3.3.2 to ensure fair comparison. Although deep learning models like CNNs and LSTMs has been widely used for EMG signal classification, they are not included in the comparative analysis due to the dataset size limitations.

Table 1 indicates Random Forest as having the highest classification accuracy of 92%. However, on the 600-window test set this value exceeds that of the multilayer perceptron (91%) by only about one percentage point, a margin that lies within the sampling variation expected for a test set of this size; the two models are therefore statistically indistinguishable on accuracy alone, and a paired significance test (for example McNemar's test) or bootstrap confidence intervals would be needed to establish a reliable ranking. Precision, Recall and F1-score follow the same trend. Although there is a difference in training time, it is ignored as the difference between models is only a few seconds, thus negligible for the intended application. Inference time remains low across all models, making them fit for the application. Random Forest was ultimately selected not on the basis of a statistically significant accuracy margin, but for its ensemble robustness to noisy, small-sample EMG data and its consistent behaviour across the reported metrics, at an inference cost that remains negligible for the system.

After the model selection, the model is train. The parameter of the model is hyper tuned using the RandomizedSearchCV, to find the best parameter for the model. The optimized parameters for the Random Forest Classifier were: bootstrap = False, max_depth = 30, max_features = 'sqrt', min_samples_leaf = 2, min_samples_split = 3, and n_estimators = 655.

Note: the inference times reported as 0 ms in Table 1 fall below the 0.01 ms resolution of the timing method used and should be read as less than 0.01 ms rather than exactly zero.

The training and test sets were formed using a stratified random split applied at the level of individual feature windows. Because the 500 ms windows were extracted with 50% overlap, adjacent windows originating from the same gesture repetition can be allocated to both partitions; the classifier may then recognise a specific recording rather than the underlying gesture, which optimistically biases the offline accuracy. This is the most plausible explanation for the gap between the 92% offline result and the markedly lower on-field accuracy reported in Section 4. The reported offline accuracy should therefore be read as an optimistic upper bound rather than an estimate of subject-independent performance. Accordingly, this work is presented as an initial feasibility study: a subject-independent evaluation using a leave-one-subject-out protocol in which all recordings from one participant form the test set while the remaining participants are used for training, rotating across participants—on an enlarged, multi-participant dataset is currently in progress and will be reported in future work.

3.3.4 Deployment

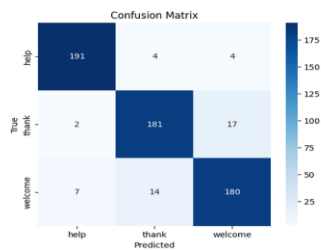
The Wi-Fi connection between the ESP32 and the MQTT broker are made before starting the web application. The application will be launch from the local browser and the output from the web application is the predicted sign and the omitted sign if the user presses the "Speak" button.

On-field testing was then conducted for the quantitative analysis of the system performance, while qualitative feedback sessions were not conducted in this phase as the main goal of the design is to test the wireless capability and latency of the MQTT protocol as a proof of concept for the system. Nevertheless, the work has incorporated comfortability factors learned from review of past works such as the use of a lightweight base glove to reduce long usage fatigue.

4. RESULTS



a. Web Page Interface



b. Confusion Matrix

Fig. 5. User Interface and Confusion Matrix of the Proposed Model

Table 2. Classification Report

	<i>Precision</i>	<i>Recall</i>	<i>F1-Score</i>	<i>Support</i>
Help	0.95	0.96	0.96	199
Thank you	0.91	0.91	0.91	200
Welcome	0.90	0.90	0.90	201
Accuracy			0.92	600
Macro average	0.92	0.92	0.92	600
Weighted average	0.92	0.92	0.92	600

Table 3. On-Field Testing Deployment Accuracy

Hand Sign	Prediction		
	<i>True</i>	<i>False</i>	<i>Accuracy</i>
Help	7	3	0.7
Thank you	6	4	0.6
Welcome	6	10	0.38

On the held-out validation windows, the Random Forest model achieves 92% accuracy, with similar performance across the classes. Help scores marginally higher than Thank you and Welcome, but all classes perform well in every metric based on Table 2 and Fig. 5(b).

The web page successfully received real-time prediction from the Random Forest model and displayed the corresponding sign label as indicated by Fig. 5(a). The “Speak Title” can be pressed to voice the label, as a medium of vocal communication.

On-field deployment is done by comparing the output from the web application with the actual hand sign done. The results shows that the system can predict the hand sign, but with lower accuracy than the classification report’s accuracy as indicated by Table 3. Aggregated over all on-field trials the mean deployment accuracy is approximately 53%, well below the 92% offline figure; this gap is analysed in Section 5 and is consistent with the window-level information leakage disclosed in Section 3.3.3.

In the on-field evaluation the “Help” and “Thank you” gestures were each tested over 10 trials, while “Welcome” was tested over 16 trials, giving 36 field trials in total. Recomputing the per-gesture accuracies directly from the recorded counts yields 0.70, 0.60 and 0.38 respectively, and an overall on-field accuracy of $19/36 \approx 0.53$; these corrected values are reflected in Table 3. The imbalance in the number of trials per gesture is a limitation of this preliminary test and should be balanced in future evaluations.

End-to-end latency, measured from the completion of a gesture to the production of the spoken output, comprises an inference component and a transport component. Model inference is effectively instantaneous, at approximately 0.10 ms per window for the Random Forest classifier (Table 1), so classification is not the bottleneck. The remaining latency is dominated by MQTT transport over Wi-Fi and by browser-based speech synthesis; a systematic characterisation of this end-to-end delay was beyond the scope of the present preliminary study and is planned as part of ongoing work, so that the wireless-transport and text-to-speech contributions can be reported quantitatively.

4.1 Sensor-Modality Ablation

To quantify the contribution of each sensing modality, a formal ablation comparing IMU-only, EMG-only and combined (EMG + IMU) configurations under the leave-one-subject-out protocol is part of ongoing work and will be reported once the enlarged dataset is available. Because the three gestures studied here are predominantly motion-based, the IMU is expected to carry most of the discriminative load; the EMG channels are nevertheless retained because they are expected to become discriminative for the static, posture-based signs, such as finger-spelled alphabets, that are targeted as the gesture set is expanded. This subsection is therefore a starting point for the sensor-fusion design rather than a definitive comparison of the two modalities.

5. DISCUSSION

5.1 System Performance

The system manages to predict SL, sending it to the web page and displaying it, allowing for seamless communication for the user. However, the deployment accuracy is low compared to the training accuracy, indicating possible flaws from noises and lack of high-quality training data. The work acknowledges the critical importance of user-centric data for a wearable communication aid. As this study represents an initial feasibility investigation, the primary focus was to validate the EMG and RF pipeline alongside measuring its reliability. In addition, the work acknowledges that the 3 participants assisting in data collection do not represent the speech-and-

hearing-impaired community. However, they were trained to execute the gestures strictly according to established sign language standards to ensure data validity.

5.2 Design Iteration

Meanwhile, the hardware design requires many improvements as the size is still big and the components are also loosely mounted on the glove, hindering good wearability. Future works should explore miniaturization of the system via the use of a flexible printed circuit (FPC), smaller form factor ESP32 variants and flexible Li-Po batteries for a smaller and thinner circuit that can conform to an arm's shape, eliminating the loose mounting issue. In addition, the gel-based electrodes must be replaced with silver-plated nylon textile electrodes to remove the need for external adhesives, making the device more skin-friendly. Lastly, the new glove must be made using specific materials. The base should use stretchable materials to ensure a tight fit and keeping the sensors firmly in contact with the skin. The inner layer must use moisture-wicking polyester to prevent short circuits from sweats, while the outer layer should be made of thicker material to protect the components from external impacts. Moreover, the testing process must include varying samples of people, including SL practitioners and additional data should be collected in relation to ergonomics and ease of use of the device.

5.3 EMG Signal Variability and Sign Language Recognition Challenges

Surface EMG-based sign language recognition system suffers from inter-subject and intra-subject variability. Inter-subject variability arises from the different physical nature of each subject such as muscle mass, electrode placement and individual execution. Intra-subject variability is influenced by inconsistency of a subject during the recording can be caused by fatigue, temporal inconsistencies during gestures, and changes in muscle contraction intensity over repeated trials.

The system utilizes dual channel EMG signal from Brachioradialis and Flexor Digitorum Ulnaris muscle and an IMU sensor to capture different activation patterns. This enhances feature variability thus partially mitigates the difference of sign language execution across different subjects. Temporal inconsistencies are addressed by segmenting the data into 500 ms windows with 50% overlap, allowing smoother representation of dynamic transitions. Time-domain features such as MAV, RMS, waveform length, and variance were selected to recognize muscle activations under non-stationary conditions. The ensemble-based Random Forest classifier contributes resilience to feature fluctuations and small dataset variability, and reduces sensitivity to noise and nonlinear outside signals.

Despite the mitigation strategies, the system still scores lower during on-field testing indicating variability still a challenge for the system. Future iterations of the system should improve the reliability of the model by adding another layer of filtering or features. Furthermore, future data collection must be conducted in collaboration with representatives from the speech-and-hearing-impaired community or at least SL experts for better validation. The current system can predict only 3 different gestures, which are all motion-based, thus reducing

the importance of the EMG sensors (a point examined qualitatively in Section 4.1, with a formal ablation planned as the dataset grows). More sign language and static hand signs such as alphabets must be added in high sample sizes to add more nuance and expand the model. Increasing sample sizes in the future will allow for deep learning models like CNN and LSTM that are more prominent in gesture recognition to be tested, as large datasets are required for avoiding overfitting and achieving stable generalization while improving the cross-subject generalization and robustness during deployment.

5.4 Cost Analysis

Affordability is a primary design objective of this work. Table 4 reports the bill of materials for the prototype, based on indicative single-unit retail prices for the components used.

Table 4. Bill of Materials for the Prototype (indicative single-unit retail prices)

Component	Specification	Qty	Unit cost (USD)	Subtotal (USD)
Microcontroller	ESP32-WROOM board	1	8	8
Surface EMG sensor	MyoWare 2.0	2	40	80
6-axis IMU	MPU-6050	1	4	4
Power	3.7 V Li-Po + TP4056	1	8	8
PCB	Custom 2-layer	1	7	7
Enclosure	3D-printed PLA	1	4	4
Glove + electrodes	Textile glove + gel pads	1	12	12
Wiring / misc.	Connectors, cabling	1	5	5
Total				128

At approximately USD 128 in single-unit component cost, the prototype is roughly an order of magnitude cheaper than the professional acquisition systems cited in Section 2: the BIOPAC MP36 and the Delsys Trigno wireless system are priced on the order of thousands of US dollars, and the prototype also remains below the discontinued Myo Armband's launch price of about USD 199. The two EMG channels dominate the cost, whereas the IMU, microcontroller and power components together contribute only a small fraction, indicating where further cost reduction should be focused. The values are indicative retail prices for single units and exclude assembly labour and fabrication overheads.

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