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A Multithreading Queuing-Based sEMG Data Acquisition System for Rehabilitation with Real-Time Visualization

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ABSTRACT

Background: Over the past two decades, myoelectric signals have been extensively used in rehabilitation technology and hybrid human-machine interfaces. A key challenge in creating self-engineered, cost-effective devices lies in acquiring reliable and accurate myoelectric signals. Additionally, identifying optimal anatomical sites for signal detection remains complex and is addressed in this study.
Methods: This applied research aims to tackle the outlined challenges through technological development and experimental testing. A Multi-Threading-based Queuing (MTQ) approach is proposed for real-time display and recording of muscle activity within a low-cost, multi-channel surface electromyography (sEMG) system. The technique was tested using raw (R) and feature (F) datasets via specialized classifiers to categorize sEMG signals from the silent utterance of English vowels captured from three facial muscles of a single healthy volunteer.
Results: The proposed low-cost sEMG data acquisition technique, utilizing MTQ, achieved a mean classification accuracy of 0.91 for both R and F datasets, surpassing previous techniques for English vowel classification. Model 4, paired with low-cost hardware, attained a remarkable mean accuracy of 0.94, showing improvements between 14.6% and 74.07% over prior studies.
Conclusion: The MTQ technique significantly enhances performance compared to existing configurations, suggesting that cost-effective sEMG data acquisition systems could replace commercial hardware in rehabilitation and human-machine interface applications.

Introduction

Over the past two decades, myoelectric signals have revolutionized applications in rehabilitation technology and hybrid human-machine interfaces. These signals, generated by muscle contractions during specific movements, provide valuable information that can enhance functional independence and improve the quality of life for individuals with impairments, especially those who have undergone laryngectomies [1, 2].

Numerous researchers have explored surface electromyography (sEMG) for its potential in detecting silent speech of English vowels using commercial or low-cost solutions. Some studies have utilized commercially available systems to acquire data and categorize human speech into five English vowels, collecting sEMG data from three facial muscles using the AMLAB workstation [3], four facial muscles with MEGAWIN equipment [4-6] and the BIOPAC MP36 system [7], and from eight muscles with a gUSBamp amplifier (gTec) in conjunction with the BCI2000 system [8]. Despite the availability of

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these high-cost commercial solutions, which also require specialized training, some researchers have developed their systems to acquire sEMG data for English vowels from three facial muscles [9-11] or the neck region [12]. However, ensuring consistent acquisition of valid signals with real-time visualization and accurately identifying optimal electrode placement points on muscles presents significant challenges in developing these systems. These challenges can lead to collecting incorrect or garbled data during recording sessions, further degrading overall system performance.

Building upon our previous research [11], this study extends a novel technology using a Multi-Threading-based Queuing (MTQ) technique designed to address key challenges in sEMG data acquisition by enabling real-time visualization and recording of muscle activity. This approach not only aids in identifying optimal electrode placement on muscles but also allows users to monitor their performance during various tasks. A primary focus of this study is the utilization of cost-effective, multi-channel sEMG signal-acquisition systems, which record electromyograms from the skin›s surface. The proposed system provides a non-invasive alternative with applications in rehabilitation, sports science, and ergonomics, assisting in diagnosing muscle disorders and monitoring muscle activity.

To validate the proposed MTQ method, we created two separate sEMG datasets: raw (R) and feature (F). Comparing the results from datasets R and F provided deeper insight into our approach›s efficacy and precision. This comparative analysis was essential for establishing the MTQ methodology›s reliability and robustness.

Methods

This study is an applied research project, specifically a technological development study with experimental elements, aimed at improving existing data acquisition setups. The focus is developing and testing a novel multithreading queuing-based sEMG data acquisition system with real-time visualization. The methodology involves data collection from a single volunteer, feature extraction, and custom classifiers for pattern recognition.

The data for this study was meticulously recorded from a healthy 40-year-old male participant with no known speech impairments and proficient in English. This participant›s data collection aimed to limit variables such as age, gender, accent, and speech fluency. The participant provided informed consent and was fully briefed on the study's procedure and purpose in accordance with the ethical code approved by the department's review committee. Recordings were conducted in a stable setting, with room temperature between 24 and 26 degrees Celsius, to minimize sweat effects, thereby ensuring data integrity [11, 13, 14].

For sEMG data acquisition, we utilized a cost-effective, three-channel MyoWare Muscle (MWM) sensor [15] integrated with the hardware developed in prior research [11]. Disposable Ag/AgCl electrodes with a 2 cm^2 gel surface were used for recording sEMG signals from three specific facial and neck muscles: the Orbicularis Oris (M1), the Masseter (M2), and the Digastric (M3) [11, 13, 14, 16]. These muscles were chosen for their potential to produce accurate sEMG data for silent speech recognition and their significance in understanding speech biomechanics.

The Orbicularis Oris, a circular lip muscle, is critical for shaping the lips during speech articulation. Due to its consistent activation patterns, it is an excellent candidate for silent speech recognition systems. The Masseter muscle, located along the mandibular ramus, contributes to robust jaw movements and displays distinct activation patterns associated with various speech sounds. Monitoring its sEMG signals can elucidate the coordination between mandibular movements and speech production. Lastly, the Digastric muscle in the neck, essential for mouth opening, plays a role in digestion and vocalization. Its involvement in silent speech recognition is based on its capacity to provide supplementary information about jaw dynamics during speech.

This study aims to improve the accuracy and efficiency of silent speech recognition systems by analyzing these muscles with sEMG technology, potentially aiding individuals with communication disorders. The MTQ method was tested using samples of softly articulated English vowels (A, E, I, O, and U) and a «Silence» condition. For reference, each vowel was assigned a unique number from 1 to 5, with «Silence» labeled as 0.

The sEMG signals acquired from the electrodes were transmitted to a computer via a serial interface for further processing. A graphical user interface (GUI) was developed using Python to facilitate signal processing and analysis. Figure 1 illustrates this interface, which includes real-time signal visualization to support efficient data monitoring and assessment.

Four control buttons—Start, Stop, Reset, and Record—were integrated into the GUI to ensure smooth data collection. The developed GUI, combined with the proposed multi-threading-based queuing (MTQ) technique for sEMG data acquisition, enables real-time visualization.

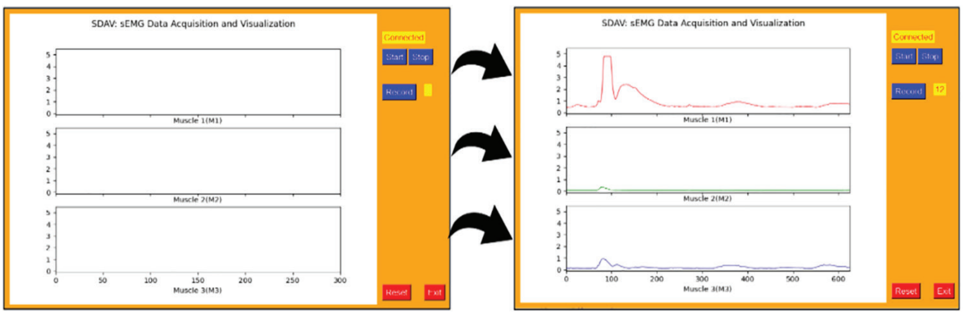


Figure 1: Screenshot of developed Graphical User Interface (GUI) with real-time visualization

This setup facilitates efficient data processing and minimizes the risk of data errors, ensuring the system can manage substantial data volumes without compromising performance. Moreover, real-time visualization offers immediate feedback to users on the data acquisition status. Figure 2 provides an overview of the entire setup.

To clarify the proposed methodology, the following provides a comprehensive exposition of the MTQ technique from an algorithmic perspective. This detailed breakdown outlines the sequential steps integral to the MTQ technique, offering a deeper understanding of its operational flow.

Algorithm **for MTQ**

```
Start
    Initialize Tkinter GUI with control buttons, record_count label, and canvas.
    Initialize master_list as an empty list of lists: [[], [], []].
    Create two queues: queue1 and queue2.
    Create thread T1 to read a line from the port and append it to queue1.
    Create thread T2 to extract a line from queue 1 and append it to queue 2.
    Create thread T3 for extracting a line from queue2, appending it to master_list, and plotting it on the canvas.
    Set the connection status (conn) to False.
    Set the button click status (cond) to False.
    while True
        Check if the hardware is connected at the specified port
            If connected, set the connection status (conn) to True.
            Otherwise, display the message "Hardware not connected" and exit the loop.
        Check if conn is True, cond is False, and the Start button is clicked
            If true, set the button click status (cond) to True and start threads T1, T2, and T3.
        Check if conn is True, cond is True, and the Stop button is clicked
            If true, set the button click status (cond) to False and stop threads T1, T2, and T3.
        Check if conn is True, cond is True, and the length of master_list[0] is equal to frame_size
            If true, prepare the data as [datetime, gender, age].
            Convert the row-wise content from master_list into the column-wise format and add it to the data.
            Append the target value to the data.
            Append the data as a row.
            Display the value of sample_count in the record_count label.
            Increment the sample_count by 1.
        Check if conn is True, cond is True, and the Reset button is clicked
            If true, set the button click status (cond) to False and clear the content of master_list.
        Check if conn is True, cond is True, and the Exit button is clicked
            If true, set the cond to False, then the conn to False, destroy the Tkinter GUI window, and exit the loop.
    Display the message "Thanks"
```

MTQ: Multi-Threading-based Queuing technique
GUI: Graphical User Interface

The procedure begins by configuring the Tkinter graphical user interface (GUI), which includes creating control elements, a label for record count display, and a graphical area for data visualization. A triple-list data structure is initialized to store visual data, with two sequential data structures (queues) set up for interim data handling. Three processes (T1, T2, and T3) facilitate data flow: T1 handles data input, T2 manages data transfer between queues, and T3 updates the visual data structure, generating a real-time graph. The size of the data structure is managed to stay within a predefined limit. The system's connection status is continuously monitored, with active data processing occurring only after successful hardware linkage and user interactions through the interface controls. The data processing phase compiles a dataset containing temporal, demographic, and measurement information, converts it into a columnar format, and updates the dataset count incrementally. System reset or termination commands prompt the necessary clean-up processes, concluding the algorithm's execution with a confirmation message.

The algorithm strategically utilizes temporal domain metrics, statistical descriptors, and integral transformations to optimize the feature vector, effectively reducing processing demands. Based on a sample size of N=900, Table 1 quantitatively represents these attributes for an sEMG signal.

We used three muscles (M1, M2, and M3) to collect at least 55 trials for each vocabulary item for dataset preparation. A minimum of 300 samples were required for each sEMG channel, totaling 900 samples per trial. This setup enabled us to effectively test and scale the application's sample capacity. We selected 50 rows from each dataset, using 900 columns from the raw dataset (R) and 10 columns from the feature dataset (F) to analyze the information contained within the sEMG recordings.

In this study, the recorded sEMG data samples were promptly allocated to a custom classification system, employing an 80-20 split for training and testing. Customized algorithms—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Artificial Neural Networks (ANN)—were utilized for pattern recognition within the R and F datasets. The KNN algorithm operates without an underlying probabilistic model, classifying new observations based on the majority label among the nearest *k* neighbors. The SVM algorithm, on the other hand, aims to establish class boundaries by constructing an optimal separating hyperplane within feature space. Inspired by the human brain's structure, ANN operates through layers of interconnected nodes, learning input-output mappings by adjusting inter-node weights. ANNs have been extensively studied in sEMG classification for their capacity to encapsulate linear and non-linear relationships. Details on the customizations of deployed classifiers are presented in Table 2 [11].

Classifier efficacy was evaluated using accuracy, sensitivity, and specificity metrics, providing insights into performance across various contexts. Accuracy measures the proportion of true predictions (both true positives and true negatives) relative to the total predictions. Sensitivity represents the proportion of actual positive cases correctly identified, and specificity reflects the proportion of actual negative cases accurately recognized. These metrics were calculated using the following mathematical formulations:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (2)$$

$$Specificity = \frac{TN}{(TN + FP)} \quad (3)$$

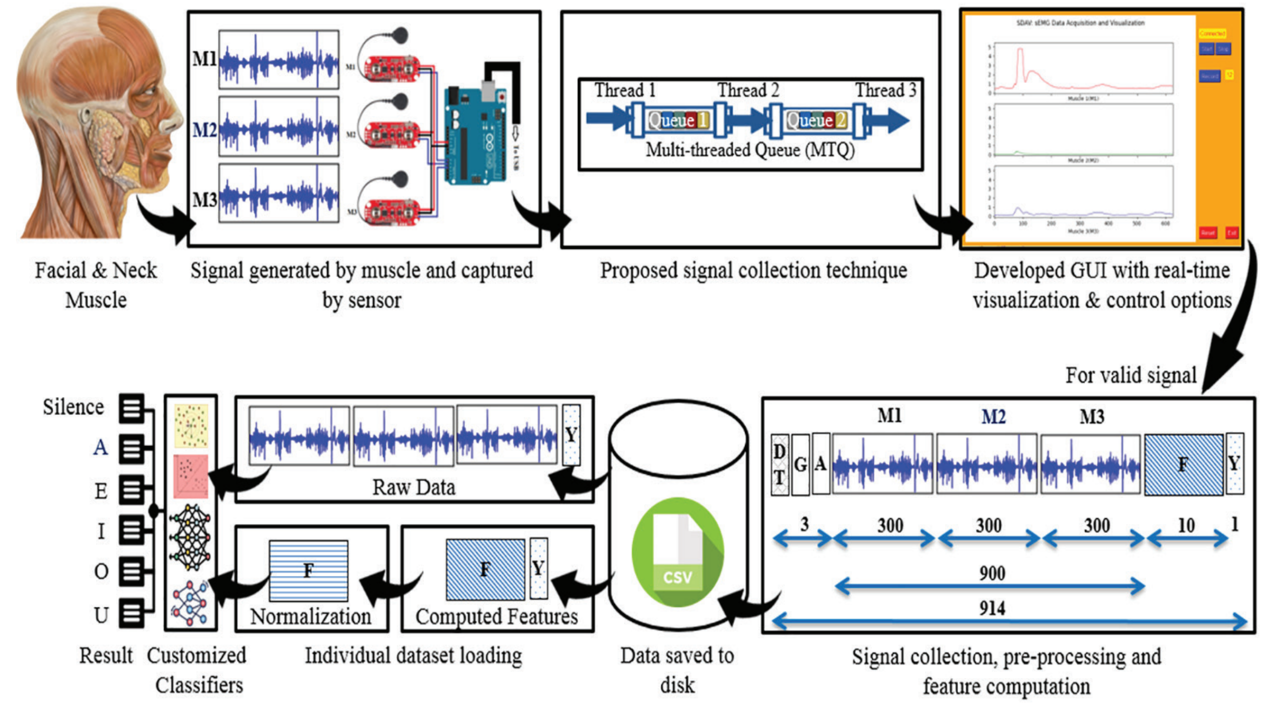


Figure 2: Here's how our technique operates: Muscular activity of the facial muscles from a healthy male subject was recorded using a MyoWare Muscle (MWM) sensor, with the developed interface displaying the signal in real time. Once a valid signal is captured, it undergoes pre-processing, and its attributes are evaluated before storage. Deployed classifiers then independently utilized both R and F datasets to identify silent speech.

Table 1: Feature representation [11]

S. No	Feature	Mathematical Formula
F1	Maximum of sEMG (MAX)	$MAX = max(x_1, x_2, ... x_N)$
F2	Minimum of sEMG (MIN)	$MIN = min(x_1, x_2, ... x_N)$
F3	Mean Absolute Value (MAV) of sEMG	$MAV = \frac{1}{N}\sum_{n=1}^{N} \lvert x_n \rvert$
F4	Median of sEMG (MED)	$MED = median(x_1, x_2, ... x_N)$
F5	Standard Deviation of sEMG (STD)	$STD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N} x_n^2}$
F6	Variance of sEMG (VAR)	$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2$
F7	Skewness of sEMG (SKW)	$SKW = Skewness(x_1, x_2, ... x_N)$
F8	Kurtosis of EMG (KUR)	$KUR = Kurtosis(x_1, x_2, ... x_N)$
F9	Root Mean Square (RMS) of sEMG	$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}$
F10	Energy (ENG) of sEMG	$ENG = \frac{1}{N}\sum_{n=1}^{N} x_n^2$

Table 2: Customization details for each classifier

Classifier	Parameters Details
Model1 (KNN)	n_neighbors=6, algorithm='auto', weights='uniform'
Model2 (SVM)	kernel='rbf', C=100.0
Model3 (ANN (100))	hidden_layer_sizes=(100), learning_rate=0.001, activation='relu', max_iter=500
Model4 (ANN (100,100))	hidden_layer_sizes=(100,100), learning_rate=0.001, activation='relu', max_iter=500

Where: TP (True Positive) - the number of positive instances successfully detected by the classifier. TN (True Negative) - the number of negative instances correctly identified by the classifier. FP (False Positive)- the number of negative examples incorrectly categorized as positive by the classifier. FN (False Negative)- the number of positive examples mistakenly labeled as negative by the classifier.

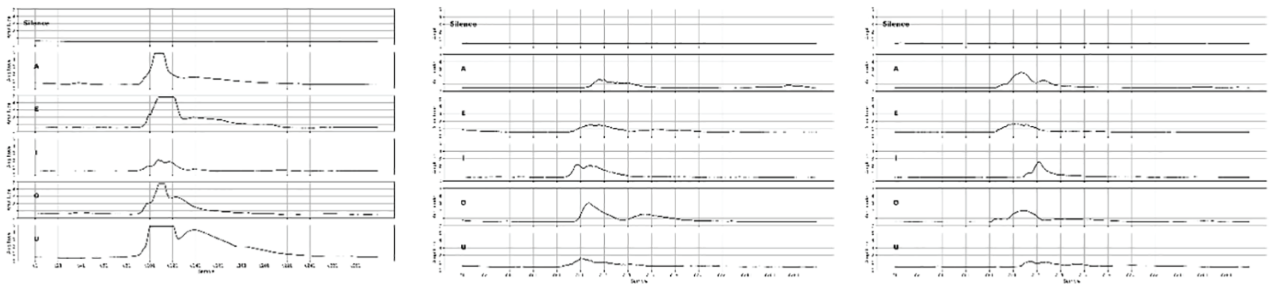
Results

The results of classifying 50 syllables using customizable classifiers are presented below. Figures 3 (a), (b), and (c) illustrate the real-time raw sEMG patterns for each vocabulary term as detected by individual muscles during the data acquisition process. Through visual inspection, it appears that each pattern is uniquely identifiable.

The R and F datasets, derived from the primary dataset, were input into the classifiers, and Table 3 displays their classification accuracy. For the R dataset using Model1, the classification accuracies for each vocabulary item (Silence, A, E, I, O, and U) are 0.95, 0.85, 0.95, 0.95, 0.88, and 0.88, respectively, resulting in a mean accuracy of 0.91 for Model1. Similarly, the mean accuracies for the R dataset with Model2, Model3, and Model4 are 0.95, 0.87, and 0.90, respectively. The overall mean accuracy for the R dataset is 0.91, obtained by averaging each model's mean accuracy.

For the F dataset with Model1, the accuracies for each vocabulary item are 0.92, 0.80, 0.83, 0.90, 0.80, and 0.78, respectively, yielding a mean accuracy of 0.84 for Model1. Similarly, the mean accuracies for the F dataset using Model2, Model3, and Model4 are 0.92, 0.93, and 0.94, respectively. The overall mean accuracy for the F dataset is 0.91, calculated by averaging the mean accuracies of each model.

Figure 4 provides a visual representation of Table 3, illustrating the performance comparison of the classification techniques for each lexical content. The results indicate that Models 2, 3, and 4 outperform Model 1 in classification tasks across the R and F datasets. For the R dataset (Type=R), Figure 4 shows a decline in sensitivity for Models 1 and 2, with values approaching 0.30 or 0.40 for each lexical content. In contrast, the F dataset (Type=F) demonstrates significant improvement in sensitivity. The F dataset also shows a lower incidence of false negatives, where positive instances are incorrectly labeled as negative. Similarly, high specificity in both the R and F datasets is associated with fewer false positives, where negative instances are mistakenly identified as positive, as shown in Figure 4.

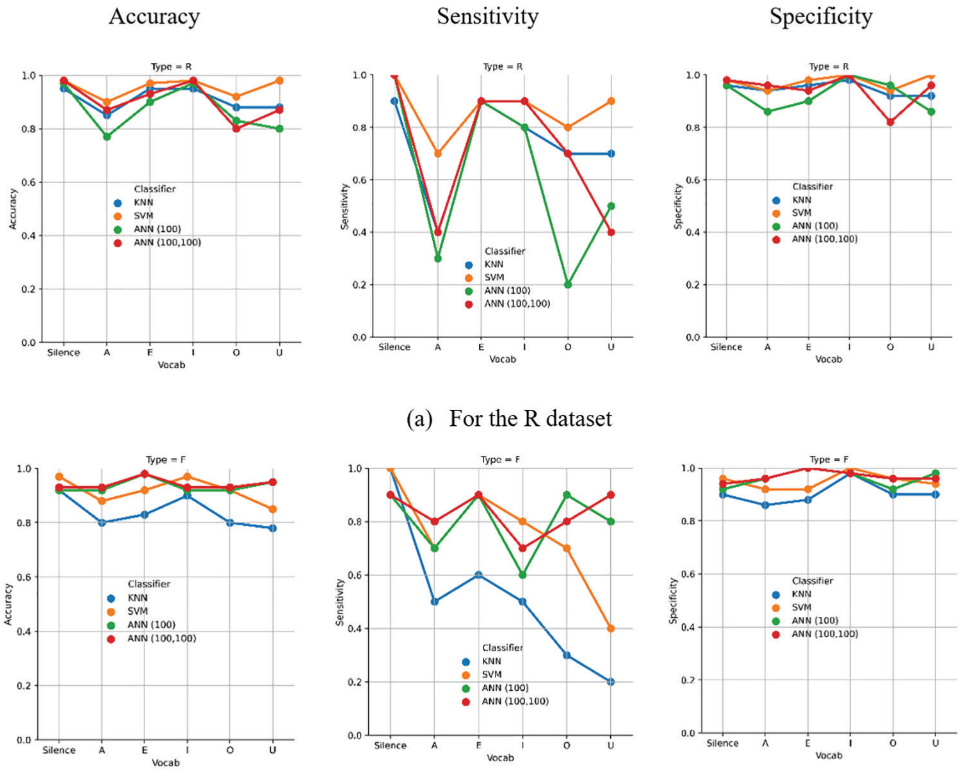


(a) For M1 (b) For M2 (c) For M3

Figure 3: Recorded Surface Electromyography (sEMG) data for each muscle

Table 3: Evaluation metrics obtained for R and F datasets for each classifier & vocab

Vocabulary	Customized Classifiers	Dataset Type	Evaluation Metrics			Dataset Type	Evaluation Metrics		
			Accuracy	Sensitivity	Specificity		Accuracy	Sensitivity	Specificity
Silence	Model1	R	0.95	0.90	0.96	F	0.92	1.00	0.90
	Model2		0.98	1.00	0.98		0.97	1.00	0.96
	Model3		0.97	1.00	0.96		0.92	0.90	0.92
	Model4		0.98	1.00	0.98		0.93	0.90	0.94
A	Model1	R	0.85	0.40	0.94	F	0.80	0.50	0.86
	Model2		0.90	0.70	0.94		0.88	0.70	0.92
	Model3		0.77	0.30	0.86		0.92	0.70	0.96
	Model4		0.87	0.40	0.96		0.93	0.80	0.96
E	Model1	R	0.95	0.90	0.96	F	0.83	0.60	0.88
	Model2		0.97	0.90	0.98		0.92	0.90	0.92
	Model3		0.90	0.90	0.90		0.98	0.90	1.00
	Model4		0.93	0.90	0.94		0.98	0.90	1.00
I	Model1	R	0.95	0.80	0.98	F	0.90	0.50	0.98
	Model2		0.98	0.90	1.00		0.97	0.80	1.00
	Model3		0.97	0.90	1.00		0.92	0.60	0.98
	Model4		0.98	0.90	1.00		0.93	0.70	0.98
O	Model1	R	0.88	0.70	0.92	F	0.80	0.30	0.90
	Model2		0.92	0.80	0.94		0.92	0.70	0.96
	Model3		0.83	0.20	0.96		0.92	0.90	0.92
	Model4		0.80	0.70	0.82		0.93	0.80	0.96
U	Model1	R	0.88	0.70	0.92	F	0.78	0.20	0.90
	Model2		0.98	0.90	0.94		0.85	0.40	0.94
	Model3		0.80	0.50	0.86		0.95	0.80	0.98
	Model4		0.87	0.40	0.96		0.95	0.90	0.96



(a) For the R dataset

(b) For the F dataset

Figure 4: Illustration of evaluation metrics obtained by classifiers for each lexical content

Table 4: Accuracy evaluation with low-cost setups

Ref	Classifiers employed		
	Model1	**Model2**	**Model4**
[11]	0.84 (Same)	0.83 (↑ 10.84 %)	0.82 (↑ 14.60 %)
[12]	0.66 (↑ 27.27 %)	0.80 (↑ 15.00 %)	0.54 (↑ 74.07 %)
Our	0.84	0.92	0.94

Discussion

In this study, the authors utilized low-cost hardware alongside the proposed Surface Electromyography (sEMG) data acquisition technique to collect and classify English vowels within a raw dataset (R) and a feature dataset (F). Both datasets showed that Model2 and Model4 outperformed Model1 regarding sensitivity and specificity (refer to Table 3). These results indicate that Model2 and Model4 are better suited for classification tasks that require accurate identification of both positive and negative instances,

To demonstrate the proposed technique's effectiveness, we comprehensively evaluated our results by comparing them to existing techniques at three levels. First, we evaluated accuracy at the dataset level, specifically comparing results from the R and F datasets. With the proposed technique, we achieved mean accuracies of 0.91 for both the R and F datasets for English vowels. For English vowel datasets, authors [8] reported mean accuracies of 0.53 and 0.75 for R and F datasets [8], respectively, while authors [11] achieved 0.82 and 0.83 for the same datasets.[11]. Our MTQ technique, however, led to notable improvements: a 71.6% increase over [8] and a 10.9% increase over [11] for the R dataset, and a 21.3% improvement over [8] and 9.63% over [11] for the F dataset. These substantial gains underscore the MTQ technique's potential to significantly enhance data acquisition accuracy for both datasets.

Secondly, we compared our results with previous studies that classified English vowels using commercial hardware configurations for the F (feature) datasets [3–8]. Our Model 4 classifier outperformed existing techniques, achieving a mean accuracy of 0.94. Compared to previous methodologies, our approach showed significant improvements across various detection rates: 6.81% over [3], 2.17% over [4], 9.30% over [5], 56.6% over [6], 11.1% over [7], and 25.3% over [8]. These findings highlight the superiority of our proposed MTQ technique for silent speech recognition and other muscle rehabilitation applications. Our method surpasses expensive commercial hardware configurations, confirming its practical effectiveness and cost-efficiency.

Thirdly, we compared the accuracy of our F dataset with similar studies that utilized low-cost hardware and self-developed algorithms for English vowel recognition. For the F dataset, our models achieved mean accuracies of 0.84, 0.92, and 0.94 with Model1, Model2, and Model4, respectively. Table 4 presents a detailed comparison of accuracy in sEMG English vowel recognition using various low-cost devices. Our F dataset outperforms those in other studies, underscoring the effectiveness and reliability of our models with low-cost hardware configurations. These findings further validate our approach's practical utility and adaptability in real-world applications.

The authors in [11] reported mean accuracies of 0.84 for Model1, 0.83 for Model2, and 0.82 for Model3, whereas the authors in [12] reported mean accuracies of 0.66 for Model1, 0.80 for Model2, and 0.54 for Model3 for the F dataset of English vowels. Our approach demonstrated significant improvements over these previously reported results with low-cost setups. Specifically, we achieved an accuracy of 0.84 for Model1, matching [11] and showing a 27.27% improvement over [12], a 10.84% improvement over [11], and a 15% improvement over [12] for Model2, and a 14.6% improvement over [11] and a 74.07% improvement over [12] for Model4. These results strongly suggest that integrating low-cost sEMG data collection devices with our MTQ technique offers a feasible alternative to expensive commercial hardware configurations, achieving high accuracy and enhancing overall system performance.

Additionally, the incorporation of real-time visualization into our technique aids in identifying optimal muscle collection points, preventing inaccurate data recording during sessions. This method's affordability and precise electrode placement support its application in rehabilitating various muscles. Furthermore, providing real-time visualization enables immediate adjustments during rehabilitation, ensuring muscles are accurately targeted and exercised. This improves rehabilitation effectiveness and minimizes the risk of additional injury or strain on the muscles.

Conclusion

This study presents advancements in Surface Electromyography (sEMG) data acquisition through the implementation of real-time visualization and customized machine learning classifiers on raw (R) and feature (F) datasets. The proposed MTQ sEMG data acquisition method significantly improved over previous techniques, achieving a 0.91 mean accuracy across both datasets for English vowel classification—a substantial enhancement from past research. Specifically, Model 4, paired with low-cost hardware, reached an impressive mean accuracy of 0.94, showing improvements ranging from 14.6% to 74.07% over earlier studies. These results underscore the superior performance of the MTQ approach in both silent speech recognition and muscle rehabilitation applications. The integration of real-time visualization also ensures accurate electrode placement and data fidelity.

Future research may further explore developing customized models for English and Hindi speakers and integrating deep learning techniques to enhance efficiency and adaptability in diverse applications.

Conflict of Interest: None declared.

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