Hand Movement Recognition Based on Fusion of Myography Signals

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Abstract: This article presents a hand movement classification system that combines acoustic myography (AMG) signals, electromyography (EMG) signals and mechanomyogram signal (MMG) data. The system aims to accurately predict hand movements, with the potential to improve the control of hand prostheses. A dataset was collected from 9 individuals who repeated 10 times each of 4 hand movements (hand close, hand open, fine pinch and index flexion). The system, with a Support Vector Machine (SVM) classifier, achieved an accuracy score of 97%, demonstrating its potential for real-time hand prosthesis control. The combination of AMG, EMG, and MMG signals proved to be effective in accurately classifying hand movements.

1 INTRODUCTION

Enhancing quality of life for people with impaired hand mobility is a major public health challenge. Advanced real-time controlled hand prosthetics offer a promising solution (Smith, 2020). However, accurately predicting hand movements under real-life conditions remains an unmet need (Johnson and Chen, 2017).

Recent advances in machine learning have created new possibilities to address this challenge (Hastie et al., 2009). Prior studies have proposed prediction systems based on electromyography (EMG) (Li and Zhang, 2013), acoustic myography (AMG) (Gupta and Patel, 2022) or MMG signals (Castillo et al., 2021). However, single modalities have limitations—EMG is susceptible to electromagnetic noise while AMG suffers from motion artifacts (Scheme and Englehart, 2011). Hybrid systems combining EMG and MMGs have shown promise (Harrison et al., 2013) but have not fully mitigated these issues.

To overcome these hurdles, we propose a novel multi-modal approach by fusing AMG, EMG and MMG signals. This provides complementary information for robust movement prediction: AMG captures muscle vibrations revealing motor unit recruitment (Mamaghani et al., 2001); EMG measures electrical potentials for high temporal resolution (Shcherbynina et al., 2023); MMGs detect limb accelerations indicating direction and speed (Al-Timemy et al., 2022). Furthermore, the multi-channel input gives machine learning algorithms more informative features to accurately discriminate movements (Farina et al., 2014a). Modality-specific artifacts also average out when the signals are combined, improving the overall signal-to-noise ratio (Lim et al., 2008). Finally, ensemble methods leveraging classifiers trained on each signal lead to higher accuracy than single modalities alone (Farina et al., 2014b).

In summary, the diversity of signal sources, the complementary nature of the information they provide, and the possibility of using ensemble methods all contribute to the potential for improved accuracy when combining AMG with EMG and MMGs for hand movement classification. Extracting discriminative features from different signal channels and effectively combining them through machine learning techniques are essential for achieving high accuracy in this field.

In this paper, we detail the development of a ma-

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chine learning model for classifying hand movements exploiting the synergistic fusion of AMG, EMG and MMGs. The proposed model could potentially be applied for real-time hand prosthesis control to improve accuracy, pending future implementation and testing. The results demonstrate promising performance towards more intuitive prosthetic control in the future.

2 DATA ACQUISITION

Dataset was collected from individuals performing four distinct hand movements: hand close, hand open, fine pinch, and index finger flexion. The integration of AMG, EMG, and MMG signals, also known as Mechanomyography (MMG) resulted in a multi-dimensional dataset primed for advanced processing.

2.1 Materials

The acoustic myography (AMG) signal was recorded using a microphone model MPA416, with a frequency range of 20-20kHz and sensitivity of 50mV/Pa. Previous literature (Orizio et al., 1989)-(Beck and et al., 2005) has shown that the frequency range of AMG signal is 5-100 Hz. To securely position the microphone and reduce signal noise (see Fig 1.), a custom 3D-printed apparatus was developed to fix the microphone on the skin surface over the target forearm muscles (Harrison et al., 2013). This minimized motion artifacts and ensured consistent AMG capture during hand movements. AMG signals were sampled at 1024 Hz.

The 3D-printed microphone enclosure (Yacoub et al.,) was specifically designed to house microphone. The base of the enclosure has a tapered shape, and the opposite end of the microphones snugly fits into the mount, thereby eliminating any distortions caused by microphone movements. Inadequate fixation of the microphone can cause alterations of the muscle signals.

The Shimmer EC69 device was used to record both the electromyography (EMG) and MMG signals. Sensors were strategically positioned on the upper arm to capture muscle activation potentials and limb acceleration. EMG signals were also sampled at 1024 Hz.

Fig. 1 shows the locations of shimmer device that was used to record both of EMG and MMG signals, with microphone which record AMG signal.

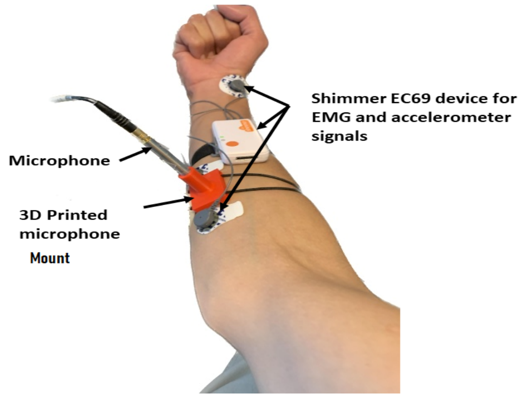

Figure 1: Channel locations on the upper forearm of the right hand of the subject.

2.2 Data Collection

To evaluate the effectiveness of combing signals for hand movement classification, a dataset was collected from 9 subjects (9 males). The mean age of particpants is 23 years. Prior to participating in the study, all participants provided informed consent and signed consent forms. The exprimental protocol was done according to the declaration of Helsinki. Fig.1 illustrate the position of each sensors. Subjects are asked to repeat 10 times four distinct hand movements: hand close, hand open, fine pinch, and index finger flexion. For exemple Fig.2 illustrates an example of a signal where one person's hand is closed, repeated 10 times.

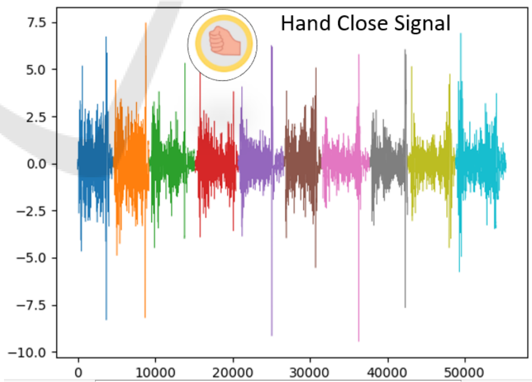

Figure 2: Example of ten repetitions of hand closure AMG Signal.

In total, the dataset comprises data from 9 subjects executing 4 distinct hand movements: close, open, fine pinch, and index finger flexion. Each movement was repeated 10 times, recorded across 5 channels (AMG, EMG, and 3 MMG), with a sampling rate of 1024 Hz. The duration of each repetition was approximately 5 seconds, and there was a rest interval of 40 to 60 seconds between movements as Fig.3 illustrates.

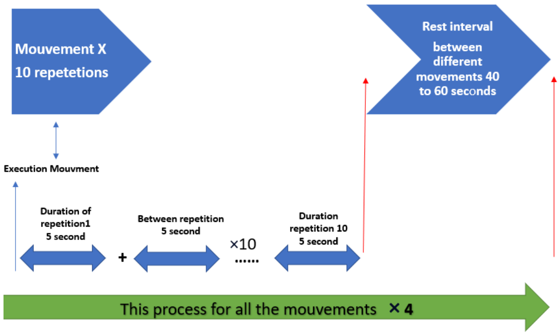

Figure 3: Execution mouvement Process.

Fig.4 illustrates the full experimental setup which integrates signals from AMG, EMG, and MMG.

Figure 4: The setup of combining AMG with EMG and MMG signals.

3 FEATURE EXTRACTION

3.1 Data Processing

The acquisition of AMG and EMG-MMG signals was done by different devices. A synchronization process is necessary to harmonize these signals. Initially, AMG data was loaded, followed by the acquisition of data from MMGs and EMG sensors (via a Shimmer device). Subsequently, the EMG signal underwent high-pass filtering, and the signal lengths among AMG, MMG, and EMG data streams were harmonized to achieve synchronization. These synchronized signals were combined into a singular variable, yielding a cohesive dataset suitable for advanced processing. As shown in Fig.5, the data streams were first loaded separately and underwent pre-processing such as filtering. They were then aligned in length and combined into a single matrix for further analysis.

Signal segmentation employed a window size of 100 samples, facilitating the division of the signal stream into discrete segments. To ensure continuous and overlapping signal segments, an intentional overlap of 50 was strategically applied, enhancing the robustness and completeness of subsequent analyses.

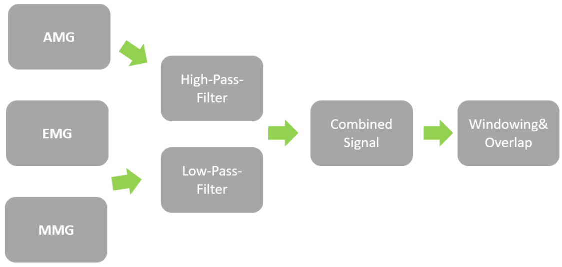

Figure 5: Preprocessing signals.

Fig. 6, it displays an example of the 5 channels (AMG, 3-channels MMG and EMG) signals recorded simultaneously during a hand movement.

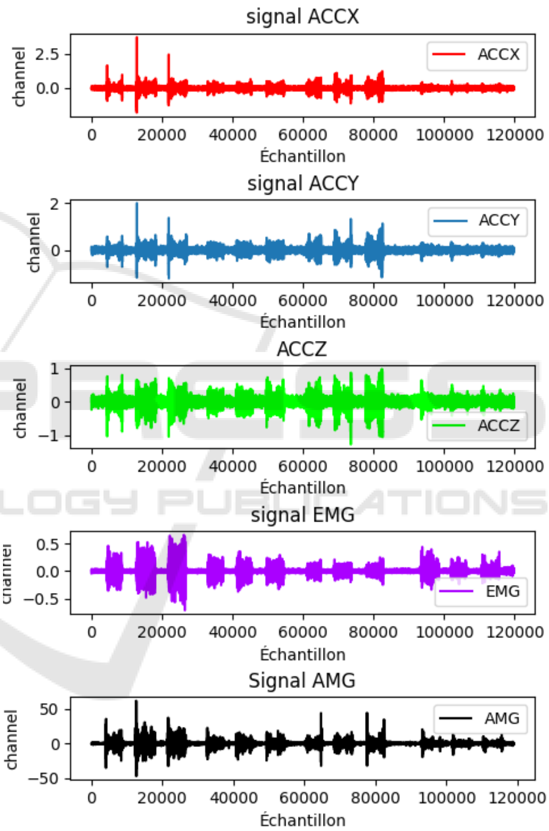

Figure 6: Example of the 5 channels AMG EMG and MMG signals.

3.2 Feature Extraction

The feature extraction process was performed using windowing and signal characteristics such as min, max, and standard deviation. The window size used was 100 samples, and the overlap was 50 to increase the amount of data for training. Each window was considered as a data sample.

Given that the signals were recorded from 5 channels (AMG, 3 MMGs, EMG), and 4 features (mean, standard deviation, min, max) were extracted from each channel per window, the total number of features extracted per window was 5 channels × 4 features = 20 features.

Therefore, the total number of samples (windows) multiplied by the number of features per sample yielded the final feature space/dimension of the dataset.

The features extracted from each window were the signal mean, standard deviation, minimum and maximum values from each of the 5 channels. These 20 features per window for each person were then normalized using standard scaling to prepare them for the machine learning model.

Summary of Feature Extraction Process	
The feature extraction in totaling 20 features per window. Multiplying this by the number of windows provided the dataset's final feature space. Each window's 20 features, capturing signal characteristics from each channel, were normalized using standard scaling for machine learning preparation	
Dataset Specifications:	
Number of Persons	9
Number of Movements	4
Number of Channels	5
Number of Features per Window per Movement	20
Number of Windows per Movement	1000

4 HAND MOVEMENT RECOGNITION SYSTEM

The methodology involves the use of sensitive microphones and EMG and MMG signals to combine signal quality. We will divide each movement into fixed-size windows and extract features from each window. These features will be used to train an SVM classifier with grid search for hyperparameter tuning (Scheme and Englehart, 2011).

Fig.7 summarizes the overall workflow. It shows the data acquisition described in Section 2, pre-processing steps of filtering and segmenting the signals detailed in Section 3.1, feature extraction covered in Section 3.2, and the classification model training. As described in Section 2, the dataset consists of signals from 9 subjects performing 4 hand movements repeated 10 times each. The data will be divided into training and test sets for each person.

4.1 Machine Learning Model

The machine learning model used in this study is a support vector machine (SVM) classifier. The SVM

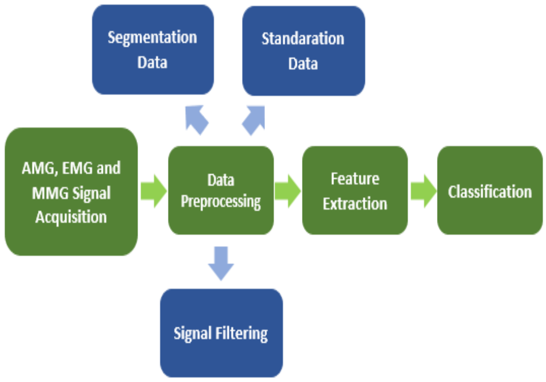

Figure 7: Model Workflow.

classifier was chosen because it has proven to be effective in various classification tasks and can handle high-dimensional feature spaces. To optimize the SVM classifier's hyperparameters, we used grid search with a range of C and gamma values. The best hyperparameters were chosen based on the highest accuracy score. To ensure the SVM classifier's optimal performance, hyperparameters such as C and gamma are fine-tuned using grid search (Hastie et al., 2009). C represents the regularization parameter that controls the trade-off between achieving a wide margin and minimizing the classification error. Gamma determines the influence of a single training example, with low values leading to a broader influence and high values causing localized influence. Grid search involves systematically searching through a predefined hyperparameter grid to find the combination that yields the best performance. In our study, we experimented with various C and gamma values to find the hyperparameters that result in the highest accuracy score on our dataset. application of a SVM classifier for signal data classification. By fine-tuning hyperparameters through grid search, we enhanced the classifier's accuracy, highlighting the significance of proper hyperparameter optimization.

5 RESULTS AND DISCUSSION

The performance metrics used to evaluate the system's performance were accuracy, precision, recall, and F1 score. After training the SVM model with grid search, we obtained the following best hyperparameters: C=10, kernel='rbf', and degree=2. The model achieved an accuracy of 97%, a recall of 97%, an F1 score of 97%, and a well-balanced confusion matrix. The analysis of results highlights the varying performance of the SVM model for different individuals and movement classes. Some individuals achieved accurate classification with high accuracy and F1-scores, while others exhibited errors in specific classes. The performance of certain individuals indicates the model's capability to generalize well for those specific individuals, while larger errors for others underscore the need for finer personalization. It should be noted that the utilization of the SVM model for movement classification based on signal data has demonstrated promising performance. The results of confusion matrices and performance measures provide valuable insights into the strengths and limitations of the model. Detailed analyses for each individual offer specific insights for targeted model improvement, such as hyperparameter tuning or individual-specific preprocessing methods. This study underscores the importance of customization and optimization of models for optimal performance.

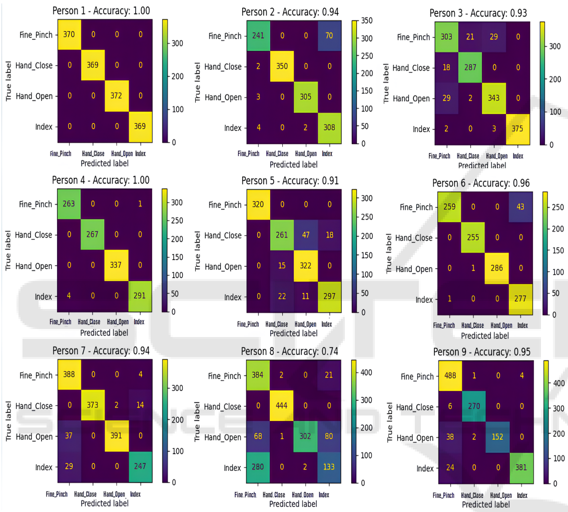

Figure 8: Confusion Matrix for Hand Movement Classification Using AMG, EMG, and MMG Signals of 9 subjects.

This table illustrates the performance metrics, including accuracy, precision, recall, and F1 score, for different individuals in the context of hand gesture recognition. It provides a comparative view of the classifier's effectiveness in recognizing various hand gestures across multiple people.

Table 1: Performance Metrics for Hand Gesture Recognition.

Person	Accuracy	Precision	Recall	F1Score
1	1.00	1.00	1.00	1.00
2	0.93	0.94	0.93	0.93
3	0.94	0.94	0.94	0.94
4	0.99	0.99	0.99	0.99
5	0.91	0.92	0.91	0.91
6	0.95	0.95	0.95	0.95
7	0.90	0.91	0.90	0.90
8	0.74	0.74	0.74	0.74
9	0.93	0.94	0.93	0.93

6 CONCLUSION

This study demonstrated the feasibility of classifying hand movements from a combination of AMG, EMG, and MMG signals using machine learning. An SVM model was able to effectively classify movements with high accuracy and precision of 97% on the test set.

The results validate the multi-model approach of fusing complementary information from different sensors. By capturing muscle vibrations, electrical potentials, and limb movements, the combined signals provided rich discriminative features for the classification model. Individual signal streams were also shown to average out artifacts when combined, improving robustness.

Further optimization of the system is still needed. Personalizing the model for each individual could help address limitations in accuracy for some movement classes and subjects. Refining feature engineering techniques may also enhance classification performance.

A key future direction is to translate this work directly into intuitive prosthetic devices. Integrating the developed hand movement recognition system could enable more natural control for upper limb prosthetics. This has potential to significantly improve quality of life for individuals with limb impairments.

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