A machine learning approach to control a Prosthetic arm via signals from residual limb - A boon for amputees

2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT) | 979-8-3503-3509-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICCCNT56998.2023.10307980

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***Abstract*— Many people have lost their hand due to accidents. This leads to upper or lower arm amputation, wrist disarticulation, trans-radial amputation, commonly referred to as below-elbow or forearm amputation. People who lost their hand face a lot of problems physically, socially and also undergo mental traumas. They were also seen as people with disabilities which makes them feel even more inferior.**

Hence, this work aims to develop a prosthetic limb or arm for individuals who have lost their hand due to accidents. Such individuals face numerous physical, social, and mental challenges and are often perceived as disabled. To address this issue, this work proposes using s-EMG signals acquired from residual arm muscles to develop an artificial hand that can be controlled through muscle movements. To achieve this, the s-EMG signal needs to be classified for different actions, as each muscle movement corresponds to a distinct pattern in the signal domain. The ultimate goal of this work is to provide individuals who have lost their hand with a prosthetic arm that functions as a natural hand and improves their quality of life.

Keywords— ***Amputation, Prosthetic arm, Arduino, Raspberry Pi, s-EMG signal, Machine learning***

I. Introduction

Forearm amputations are a life-altering experience that is typically caused by sudden accidents and unexpected trauma. These events are often associated with injuries, and it is essential to address any systemic issues before considering prosthetic solutions. In a world with a population of 6.7 billion people, there are approximately 10 million amputees, of which 30% (3 million) are armed amputees. Although the number of amputees in developed countries is lower, there are still 2.4 million amputees in developing countries [1]. Furthermore, amputees below the elbow account for 58% of all arm amputees, and approximately 23,500 new amputees are added each year [2]. Therefore, this work aims to provide an affordable prosthetic arm that meets the basic needs of amputees.

Recent technological advancements have played a critical role in acquiring bio-signals, with surface electromyography (s-EMG) being one of the most significant breakthroughs [3]. This signal is generated by muscular activities such as contraction and relaxation, and it can be acquired from muscles using Ag/AgCl electrodes placed on the muscle's surface. However, the s-EMG signal extracted is noisy and of low amplitude, requiring a series of pre-processing steps before further classification. One practical application of s-EMG signals is the development of prosthetic limbs for below elbow and mid-forearm amputees. These prosthetic arms function based on the s-EMG signals acquired from the muscles of the residual arm. To control the prosthetic arm, the s-EMG signal must be classified for different actions since each muscle action replicate a unique pattern in the s-EMG signal. The prosthetic arm aims to reduce the risk of individuals being vulnerable to physical disability and to ensure their safe mental and social health.

This approach presents an accessible and economical method for the development of a functional prosthetic hand that can be tailored to meet the unique needs of individual users. The use of 3D printing allows for quick and affordable customization of the prosthesis, while the classification of the s-EMG signal offers an intuitive and efficient method for control of the prosthetic hand. Overall, this work demonstrates the potential of using modern technologies for the advancement of prosthetic devices, providing an opportunity for improved quality of life for amputees.

Many researchers have attempted s-EMG based prosthesis using signal processing and deep learning techniques for effective use of prosthetic arm design. This thus improves the quality of life of amputees [4-6].

II. METHODOLOGY

The proposed system is a hand prosthesis designed to perform different types of grasping actions, which is 3D printed using an inexpensive fused deposition modelling machine. The main design concept of the prosthesis consists of 5 moving fingers, each driven by servo motors, and connected to the motor using wire. The prosthesis is controlled using a dual channel s-EMG signal acquired from the amputee's muscle with an STM32 microcontroller and Olimex EMG Shield.

The acquired signal is then pre-processed with bandpass filter frequency ranging from 5Hz to 100 Hz. The signal processing and classification are performed in a Raspberry Pi, time domain features from the signal are extracted for classification for a predefined set of actions. Once the signal is classified into a predefined set of action, the servos present in the 3D printed prosthetic hand are rotated as per the action to exact the same action performed by the user. Fig. 1 illustrates the flow diagram for signal acquisition and classification of hand actions.

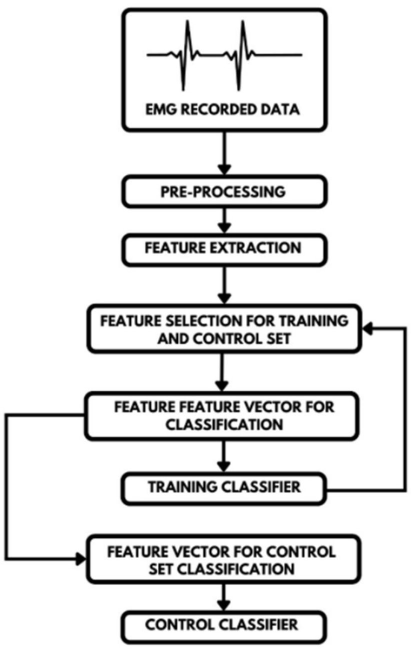

Fig. 1. Flow diagram for signal acquisition and classification of hand actions

In order to effectively control a prosthetic arm using EMG data, a multi-step process is typically employed to develop a suitable machine learning (ML) model that can classify the EMG signals associated with various hand actions. This process generally involves several key steps, including signal acquisition, data preparation, feature abstraction, and training of model

A. 3D Modelling

Two types of hand models that serve different functions. The first model shown in Fig. 2 (a) is intended for performing day-to-day actions, while the second presented in Fig. 2 (b) is intended for object handling.

To create these hand models, different materials have been used based on their suitability for each model's specific needs. Acrylonitrile Butadiene Styrene (ABS) is used for the first model. This is a thermoplastic polymer known for its strength, durability, and resistance to impact [7]. These properties make it an ideal material for the hand model that will be used for day-to-day activities.

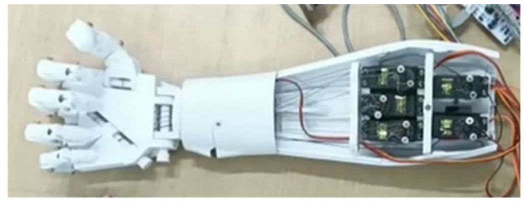

Fig. 2 (a). Intended for performing day-to-day actions

Polylactic Acid (PLA) has been used for the second model, which is a biodegradable and bioactive thermoplastic made from renewable resources such as cornstarch or sugarcane [8]. PLA is a suitable material for the hand model used for holding and manipulating objects because it is less rigid than ABS and offers greater flexibility, making it easier to grasp and manipulate objects.

Fig. 2 (b) Intended for object handling

Additionally, for the finger index connectors of the second model, Thermoplastic Polyurethane (TPU) has been used, which is a highly elastic and durable material [9] that provides a secure connection between the fingers and the hand model.

B. s-EMG Acquisition

In order to collect the necessary data for the development of a prosthetic arm control system, the Olimex Shield EKG-EMG with two channels of electrodes is employed. Fig. 3 illustrates the placement of the electrodes on the relevant muscles, including the reference electrode.

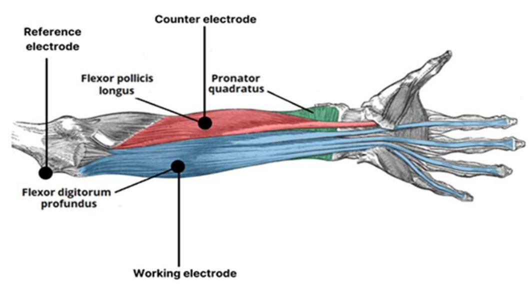

Fig. 3. Placement of the electrodes on the relevant muscles

During data collection, the flexor digitorum profundus muscle is used as the working electrode, while the flexor pollicis longus muscle serves as the counter electrode. This arrangement allows for the acquisition of reliable EMG signals, which can be used to develop a machine learning model capable of classifying various hand actions for the control of a prosthetic arm. Fig. 4 illustrates the connection between Olimex Shield EMG-EKG and STM32 Nucleo. Pins A0 and A1 are used to record the analog serial EMG values.

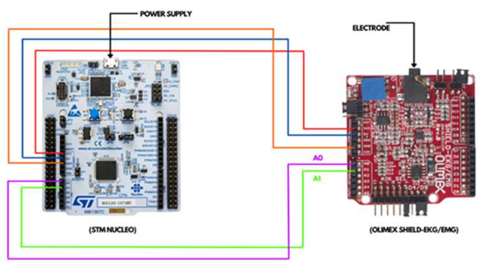

Fig. 4. Connection between Olimex Shield EMG-EKG and STM32 Nucleo.

During the data collection process for the development of a prosthetic arm control system, four basic hand actions are considered: open, close, extension, and flexion. Fig. 5 illustrates the four basic hand actions considered. These actions serve as the foundation for the generation of all other general hand actions. By collecting data on these four basic hand actions, a ML model can be trained to accurately classify and differentiate between various hand movements, ultimately allowing for the precise control of a prosthetic arm.

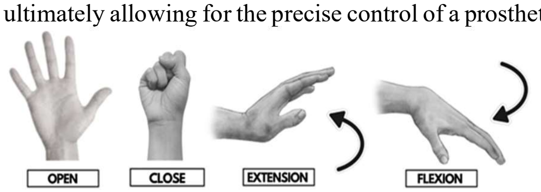

Fig.5. Illustration of the four basic hand actions considered

C. *Random forest classifier*

A powerful machine learning algorithm for classification tasks that combines multiple decision trees to make accurate predictions [10]. Each decision tree is constructed using a random subset of the training data and a random subset of features. During training, each tree independently classifies the input data and the final prediction is determined by majority voting among the trees. This ensemble approach helps to reduce overfitting and improves the overall predictive performance. The modeling equation for a random forest classifier is presented in Eqn. (1).

$$y = f(x) = argmax(voting(T_1(x), T_2(x), \dots . T_n(x))) \tag{1}$$

where y represents the predicted class label for input x
f(x) denotes the overall prediction of the random forest classifier
$T_1(x), T_2(x), \dots . T_n(x)$ are the individual predictions of each decision tree in the forest
Argmax returns the class label that occurs most frequently among the predictions.

III. RESULTS AND DISCUSSION

The corresponding EMG signals are recorded for each basic hand action and further analysis is performed. The analysed data values are used to train and develop machine learning models that classify and differentiate between various hand movements, ultimately enabling precise control of a prosthetic arm.

Fig. 6 illustrates typical representation of the s-EMG signal. The complete s-EMG signal for close action is shown in Fig.6, where the signal burst corresponds to the contraction phase, and the non-burst section represents the relaxation phase.

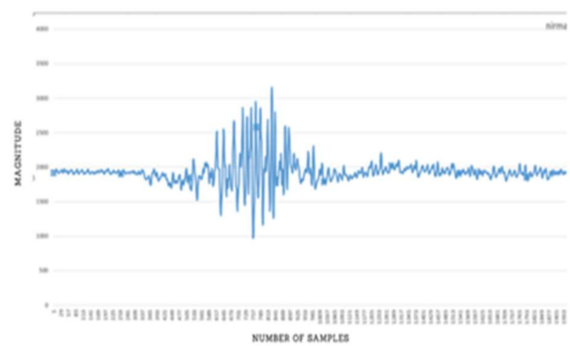

Fig. 6. Typical representation of the s-EMG signal

A. *Data Collection*

The present study involved the collection of a substantial amount of data, specifically a total of 2192 datasets. The data was gathered from 543 individuals, who varied in age from 16 to 60 years old. These individuals participated in the data collection process, and their actions were recorded in relation to hand movements. A rest-action-rest pattern was recorded from the subjects. It is important to note that each distinct hand action was associated with a total of 543 datasets, indicating a thorough and comprehensive data collection process. Overall, this study involved a significant amount of data, which contributes to the robustness and validity of the findings.

B. *Filtering*

In order to effectively smoothen the s-EMG signal and eliminate unwanted noise, it is necessary to filter the signal. The power spectral density plot of the raw sEMG signal is shown in Fig. 7. It is evident from Fig. 7 that the signal's main frequency falls between 5 Hz and 100 Hz.

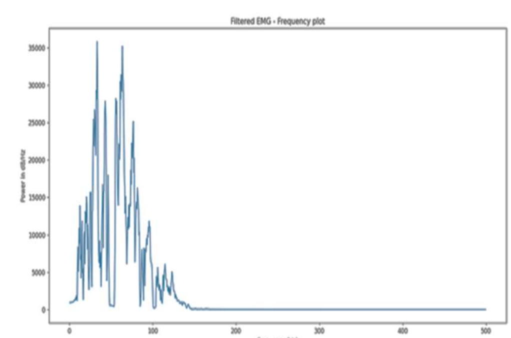

Fig.7. Power spectral density plot of the raw sEMG signal

As a result, a bandpass filter is employed to remove all other frequencies and ensure that the range between 5 Hz and 100 Hz is considered. The difference between the raw s-EMG signal, and the filtered signal with a bandpass filter, are both depicted in the Fig. 8. This process is critical in guaranteeing that the sEMG signal is properly filtered and smoothed for further analysis.

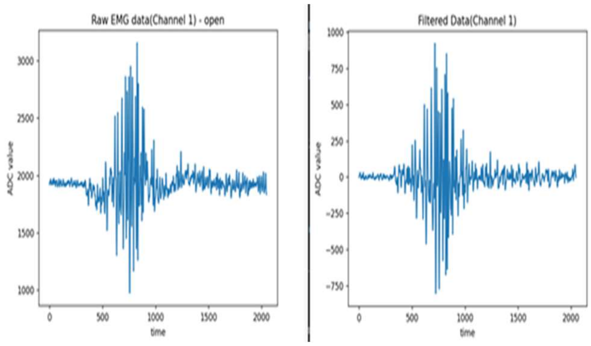

Fig.8. Difference between the raw sEMG signal and the filtered signal with a bandpass filter

C. Feature Extraction

In order to train the classifier, features are derived from the pre-processed sEMG signal. Various features extracted from the signal include zero crossings, mean absolute value, integrated EMG, slope sign change count, Wilson amplitude, root mean square, slope sign changes, and waveform length [11, 12]. The list of the parameters used and their corresponding characteristics in s-EMG signal are tabulated in the Table 1.

These features are critical for the training of the classifier as they provide important information about the signal and allow for accurate classification.

Table 1. Features and their characteristics

FEATURE	DESCRIPTION
Mean Absolute Value (MAV)	Average amplitude of the EMG signal.
Integrated EMG (IEMG)	Total amount of electrical activity generated by a muscle over a certain period of time.
Zero Crossing Count (ZCC)	Number of attempts the EMG signal crosses the zero baseline.
Slope Sign Change Count (SSC)	Number of times the slope of the EMG signal alter its sign.
Root Mean Square (RMS)	Overall amplitude of the EMG signal.
Wilson amplitude	Amplitude of the EMG signal at the peak of a muscle contraction.
Waveform Length (WL)	Total length of EMG signal over a specific time window.

D. Classification of Hand Actions

The development of a prosthetic arm control system involves the training of 14 machine learning algorithms using extracted features.

These algorithms include decision tree, logistic regression, gradient boosting, and others. The dataset is split into 70% for training the models and 30% reserved for testing to compare the accuracy of each algorithm. The accuracy of each algorithm is compared, and those with better accuracy are selected.

Table 2. Model performance for classification with 50 epochs

MODEL	Train Accuracy	Standard Error	Test Accuracy
RNDFOREST	0.84	0.099778	0.92
LDA	0.666667	0.126491	0.8
ADABOOST	0.84	0.090431	0.76
CART	0.8	0.10328	0.76
SVM - Linear SVC	0.773333	0.099778	0.68
LOGISTIC REGRESSION	0.68	0.06532	0.68
KNN	0.666667	0.111555	0.84
GRADBOOST	0.733333	0.126491	0.72
QDA	0.626667	0.116237	0.64
SVM - NuSVC	0.56	0.161107	0.64
SGDC	0.52	0.088443	0.68
Bernoulli - NB	0.48	0.148474	0.6
SVM - SVC	0.44	0.116237	0.6
AdaBoost	0.84	0.090431	0.76

This process is critical in determining the effectiveness of the machine learning algorithms in accurately identifying the intended hand actions based on the extracted features from the pre-processed sEMG signal. Model performance for classification with 50 epochs training is tabulated in the Table 2.

Table 3. Model performance comparison for binary - 1 classification task

ALGORITHM	Precision (0)	Recall (0)	F1 (0)
RNDFOREST	0.87	0.93	0.9
LDA	0.74	1	0.85
ADABOOST	0.79	0.79	0.79
CART	0.79	0.79	0.79
SVM - Linear SVC	0.61	1	0.76
LOGISTIC REGRESSION	0.82	1	0.9

Comparing the top six models with highest accuracy, Table 3 & 4 illustrates the performance metrics of different machine learning algorithms on a binary classification problem. The algorithms are evaluated on Precision, Recall, and F1-Score [13] for both classes 0 and 1. Table 5 illustrates the algorithm performance and confusion matrix on test data.

Table 4. Model performance comparison for binary - 0 classification task

ALGORITHM	Precision (0)	Recall (0)	F1 (0)
RNDFOREST	0.87	0.93	0.9
LDA	0.74	1	0.85
ADABOOST	0.79	0.79	0.79
CART	0.79	0.79	0.79
SVM - Linear SVC	0.61	1	0.76
LOGISTIC REGRESSION	0.82	1	0.9

In summary, the Random Forest algorithm seems to perform well on this particular binary classification problem, with high precision, recall, and F1-Score for both classes. However, the choice of algorithm depends on particular needs of the problem and other influences such as dataset size, computational resources, and model complexity.

Table 5. Confusion matrix on test data

MODEL	CONFUSION MATRIX
RNDFOREST	[[232 10] [73 185]]
LDA	[[208 42] [108 142]]
ADABOOST	[[195 60] [81 164]]
CART	[[212 40] [68 180]]
SVM - Linear SVC	[[238 10] [100 152]]
LOGISTIC REGRESSION	[[236 10] [80 174]]

Once the machine learning model is constructed, the real-time s-EMG signal is captured from the subject's muscles through electrodes. The signal undergoes pre-processing to remove any noise that may exist. The relevant parameters are then derived from the pre-processed signal and used as inputs to the machine learning model to identify the intended hand action. The identified hand action is subsequently transmitted to the embedded controller, which controls the end effector. This entire process ensures that the subject's intended movements are translated into actions by the end effector, improving the overall effectiveness and precision of the system. Fig. 9 depicts the process of performing the hand actions in the end effector.

IV. CONCLUSION

The loss of a limb due to accidents can have profound physical, social, and mental impacts on an individual [14]. To address the numerous challenges faced by individuals who have lost their hand, the development of a myoelectric prosthetic arm using a machine learning approach to control it via signals from the residual limb has immense potential to transform their lives. By providing a more intuitive and natural control method for the prosthetic arm, this technology could significantly improve the quality of life for individuals who have suffered from limb loss

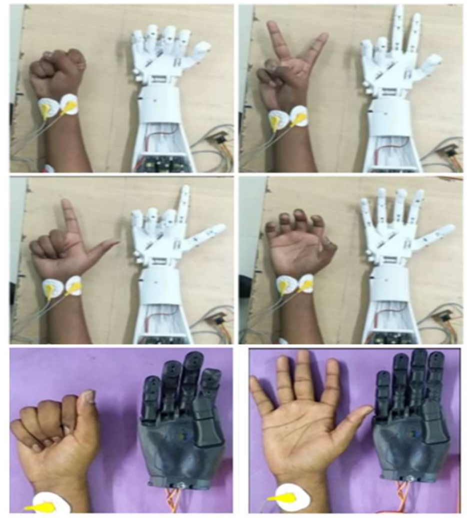

Fig. 9. Performing different hand actions

In addition to addressing the physical challenges of performing daily tasks, such as grasping and manipulating objects as illustrated in Figure 11, this technology has the potential to alleviate the social and mental burdens of limb loss. Individuals who have lost their hand may experience social isolation, difficulties in maintaining relationships, and a diminished sense of independence. By providing a prosthetic arm that functions as a natural hand, this project could provide them with a sense of normalcy in their daily lives, thereby improving their overall mental and emotional well-being.

Furthermore, this project could potentially provide a more affordable and accessible solution for individuals who require prosthetic limbs, especially in developing countries. Traditional prosthetic limb control methods, such as switches or joysticks, can be challenging to use and may require extensive training. In contrast, myoelectric control using machine learning algorithms can be more accurate and precise, allowing for a more natural and intuitive control method.

Overall, the development of a myoelectric prosthetic arm controlled via signals from the residual limb has the potential to revolutionize the lives of individuals who have suffered from limb loss. By addressing the physical, social, and mental challenges associated with limb loss, this technology could significantly improve their quality of life and provide a more accessible solution for those who require prosthetic limbs.

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