International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

# Simulation of Artificial Intelligence based Robotic Arm for Patients with Upper Limb Amputations

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**Submitted**: 05/02/2024 **Revised**: 13/03/2024 **Accepted**: 19/03/2024

**Abstract:** A myo-electric controlled prosthetic extremity is a prosthetic limb that seems to be controlled but is really controlled by electrical signals that the muscle structure itself automatically delivers. Electromyography is a novel method for recording and analysing electrical activity generated by muscles. Computerized reasoning and machine learning are particularly impressive in the mechanical and biological sciences. The purpose of this work is to apply artificial intelligence to predict and comprehend prosthetic hand movements using muscle training data. This idea already exists in the mechanical world, but it is prohibitively expensive and unavailable to non-industrialized countries. As a result, the primary goal of our research is to develop the much more precise intelligent bionic hand. In this research, also used MyoWare Muscle Sensor data, a tool that continually analyses information from eight sensors are also employed. Artificial intelligence and the informative index were used to anticipate finger, finger-close, round grip, and satisfactory-squeeze impulses. We It is next applied a few Artificial intellogence computations to the statistics verified with the 8-terminal superficial Electromyography MyoWare Strength Detector, including K-closest Neighbor (KNN), Support Vector Machine (SVM), and a mixture of SVM and KNN. In this research it is further characterised the four demonstrations of our prosthetic hand with a unceasing test accuracy of 98.33 percent by merging SVM and KNN. This report also includes a 3D visualisation of the robotic finger and its control strategy using Autodesk 3D's Max software design, an EMG MyoWare Muscle Sensor, Artificial intelligence.

***Keywords:*** *Artificial intelligence, robotic arm, electromyography, sensors*

## 1. Introduction

Artificial intelligence (AI) has the potential to revolutionize the field of prosthetics and assistive devices for patients with upper limb amputations. By using machine learning algorithms and advanced sensors, AI-controlled robotic arms can provide a high level of customization and adaptability to meet the specific needs and preferences of each individual user (Ortiz-Catalan et al., 2020). One potential application of AI in the field of prosthetics is the development of robotic arms that can be controlled by the user through various input methods. For example, electromyography (EMG) sensors can be used to detect muscle signals from the remaining limb of a patient with an upper limb amputation (Miao et al., 2021). These signals can then be translated into movements of the robotic arm through the use of AI algorithms (George et al., 2020).

In addition to EMG sensors, other input methods such as joysticks or touch screens can also be used to control the movement of the robotic arm. By using a combination of these input methods, patients can have more control over the movement and position of the arm, allowing for a greater range of motion and flexibility (Sun et al., 2022). One of the key benefits of AI in the development of prosthetic arms is the ability to learn and adapt to the movements and preferences of the user. Machine learning algorithms can be used to analyze data from the input signals and the movements of the arm, allowing the system to learn and improve over time. This can result in a more intuitive and natural control of the arm, as it can adapt to the user's specific needs and movements (Jiang et al., 2022). In addition to the ability to control the movement of the robotic arm, AI can also be used to enable the arm to perform a variety of tasks and functions. For example, the arm could be equipped with sensors and algorithms that allow it to recognize and manipulate objects in the environment. This could include tasks such as picking up and holding objects, turning doorknobs, or operating

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electronic devices. The use of AI in the development of prosthetic arms can also help to improve the overall functionality and usability of the device (Müller & Sawodny, 2022).

For example, machine learning algorithms can be used to analyze data on the performance and usage of the arm, allowing for the identification of any problems or issues that may arise. This can help to improve the reliability and durability of the device, and can also help to identify any potential areas for improvement or further development (K. Li et al., 2023). In conclusion, the use of AI in the development of prosthetic arms for patients with upper limb amputations has the potential to greatly improve the functionality and usability of these devices. By using machine learning algorithms and advanced sensors, AI-controlled robotic arms can provide a high level of customization and adaptability to meet the specific needs and preferences of each individual user. This can result in a more natural and intuitive control of the arm, as well as a wider range of tasks and functions that can be performed (Luo et al., 2022).

According to one study, electromyography data might be recognised and analysed using neural networks. The first adjusts and aggregates the EMG data, while the second assesses the anatomical patterns of the brain (Zheng et al., 2023). SMA is used in place of EMG signals since it is lighter and smaller. Modifications to prosthetic limbs are suggested. Three parts make up this study: the first examines how EMG signals affect computer simulations, the second examines the same topic, and the third examines a variety of virtual hand models that use EMG signals. The fingers, arm, and foot all point in the same direction, claims another study. People can communicate with the rest of the world thanks to it (Yan et al., 2022). A vibration signal from a gyroscope was used to record competent people tapping on variously hard surfaces in order to approximate the best robotic prosthesis handling technique. The tips of both feet perform better than a higher limb to provide this vibrating input. How to use a certain kind of tactile stimulation with cutting-edge control techniques (Zhuojun et al., 2015).

To offer feedback on grasping motions in this instance, the electronic elbow provision is used in combination with connection forces and moments throughout the arm (Wang et al., 2022; Yang et al., 2022). Both forearm movements excite the EMG. This may reflect power with reticular formation and power with reticular formation biceps myoelectric signals, and it can be used to accurately identify artefacts in a range of conditions, both with and without pressure control. In this situation, sensory feedback is significant. Its tests on seven healthy individuals produced positive results. In a subsequent investigation, data from the top portion of an appendage that generated energy while using a security appendage were collected using a surface electromyogram. They experimented with numerous methods and alternatives to calculate the proper wrist.

Additionally, they saw a few discrete isometric right-hand talents that matched the expected level. The authors claim that an EMG signal might control a prosthetic limb (Xu et al., 2023; Ye et al., 2023). The EMG-signal excitement is ended by AI in the physical scheme and anode implantation in the muscles. The distal and proximal higher attachment materials with EMG activity are utilised to anticipate various hold signals, including handle signals, using the vector machine technique. Support vector machines are important for creating prosthetic devices because they can recognise EMG signals rapidly and consistently, according to recorded data and validation. To perform multiclass classification, features are extracted from EMG signals and supplied into a linear SVM. In order to forecast and recognise hand gesticulations from muscle activity (H. Li et al., 2022; Liao et al., 2021; Sherwood et al., 2022).

By obtaining publicly available connected Electromyographic (EMG) signals, pre-processing the data, identifying topographies, and using artificial intelligence classifiers and deep learning models, it is feasible to attain an offline test accuracy of 80% to 90%. Using common machine learning techniques and feature removal on data collected for the purposes of this study, two amputees achieved a current test accuracy of 95% in classifying separate finger actions.

## 2. Proposed System

In line with our future strategy, at first collect factual data are collected utilising an EMG signal. Following that, the pre-handle such indications in various ways and extract their components are made. From then,the informative index is combined to determine the most reliable movement perception reward. features are applied to the model to test its accuracy.

On the surface, there seems to be a willingness to participate in solitary activities. Electromyography is required to understand the hand's movement architecture. The study of the RSME upsides of modified gestures to edges, based on the structure of turmoil of respectively channel's mean strength, has been used to expose the muscle's preparation here and there utilising a limit framework. The voltage reference was also removed when the set was computed (Liu et al., 2023; Tsegay et al., 2022).

When our brain is activated, it transmits a signal to one of our muscle tissues, causing us to react. As seen in Figure 1, the signal then travels from the body's brain stem to the main nerve cell of the appropriate muscle. When the brain activates a motor neuron, an electrical signal is delivered across the entire length of the muscle, resulting in action potentials, that are phases of polarisation and depolarization. The signal causes motor neuron cells in the muscle to activate, causing the muscle to contract by activating all of the sarcolemma along the neuromuscular strands. The action potential is captured during an electromyography session. Electromyography has a variety of uses. The greatest significant usage of electromyography is therapeutic diagnostics, which informs us about the sorts of signals that muscles create in the event of aberrant muscular activity.

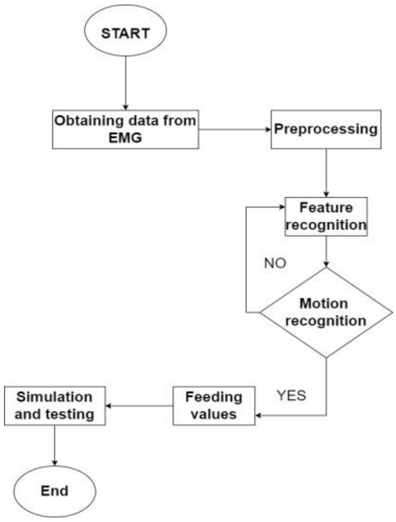


**Fig 1.** Flowchart of the proposed system

The goal of this study is rehabilitation, as well as a novel application of EMG and prosthetic limb control. This is utilised in biomechanical study, among other things, to understand more about how our brains regulate our muscles. Image 1. Surface electrodes and intramuscular electrodes are the two most often used electrode types in electromyography. Figure 2 demonstrates the use of surface electrodes in this experiment, which are often used in other procedures such as EKGs and EEGs. They are really easy to use since they can only be utilised by attaching to the skin.

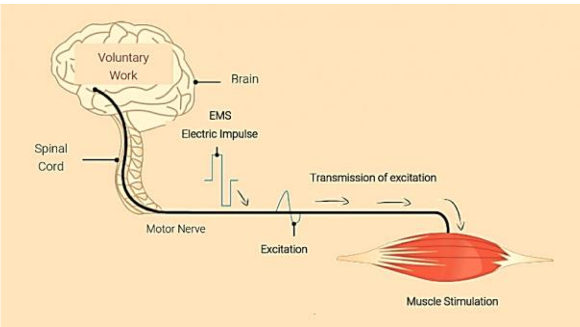


**Fig 2.** Muscle function

## 3. Working Methodology and Evaluation of the EMG Based Bionic Arm

An EMG-based bionic arm is a type of prosthetic arm that is controlled by the user's muscle signals. The arm is equipped with sensors that detect the electrical activity of the user's muscles, which are then used to control the movement of the arm. To use an EMG-based bionic arm, the user must first undergo surgery to have electrodes implanted in their muscles. These electrodes detect the electrical activity of the muscles and transmit the signals to the bionic arm. The bionic arm is equipped with a control system that interprets the muscle signals and translates them into specific actions. For example, if the user wants to move their bionic arm to grab an object, they would tense the muscles in their chest or arm, which would trigger the electrodes to send a signal to the control system. The control system would then interpret this signal as a command to move the arm and would send a signal to the motors that control the arm's movement. The bionic arm is also equipped with sensors that provide feedback to the user, such as touch or temperature sensors that allow the user to feel the objects they are handling. Overall, the working principle of an EMG-based bionic arm is to use the electrical activity of the user's muscles as a means of control, allowing the user to perform tasks and movements that would not be possible with a traditional prosthetic arm. Figure 3 shows the bionic arm developed in this research.


,

**Fig 3.** Robotic arm developed in this research

**The artificial computation evaluation used in this research to test the developed bionic arm are as follows:**

### 3.1 Dataset

Each dataset comprises the real time monitoring of 8 sensor. This results in a total of 64 EMG datasets. The final column contains the result action, which would be derived from the data supplied for classes 0 through 3. As a result, every one of the following phrase is formatted as follows: Because the data was collected at a frequency of 200 Hz, the determination is to remove any unsolicited noise that may have corrupted the signal. This appears to be critical since if left unchecked, it will have an impact on the information that we evaluate. The frequency range of most EMG impulses is between 20 and 350 Hz. That is, a heartbeat with a frequency below 20Hz or greater than 350Hz creates someplace other than a muscular. The sound might be caused by electrode activity or a specific high frequencies broadcast from smart phones and radio wave transmission.

### 3.1 Support Vector machine

SVM is a twofold classifier that determines if an instance belongs to one of two classes. It follows the rule of increasing underlying hazards that jeopardise tactical tricks and the model's difficulty. The creation of a excellent superficial is an essential component of an SVM in order to improve the distinction of both optimistic and negative models. Because Rn parts are information vectors, the judgement surface has an indisputable level. For information that can be seen immediately away, it is best to separate it with an optimum divider line.

Typically, support vector machine (SVM) is a simple and relatively intuitive idea. Despite this, when the vector fields are detachable, problems occur. The issue emerges once the information point reductions into the gap amid the perfect hyper planes and the information co-ordinates are displayed crossways hyper planes. A adjustable I is utilised to construct the support vector machine computation, which is accountable for deviations after the data point's perfect location. As a result, the accompanying optimization technique may concisely characterise the basic principle of an SVM.

### 3.2 K-Nearest Neighbor

The K-Nearest Neighbor (KNN) algorithm is crucial for recognising designs. By using this method, same things that are near to one additional are found. It is primarily used to address relapsing and organization issues which call for expectancies. Due to its simplicity in translating and quick estimation duration, the KNN technique offers an excellent assumption overall. KNN ordering is employed to carry out factual inquiry utilising a classifier job whenever stable normative evaluation is highly hazy or deciding is difficult. We used this method to enhance the result since our proposed model includes data on human movement. Electromyography (EMG) signals impact artificial hand grasping and grip opening, which are created by a variety of components of diverse test subject movements using the KNN rule. The pretense distance or flap measured may be used to improve outcomes. The green dot in the test sample should be recognised as first class, while the red, blue, square, or triangle should be recognised as second class. Because it contains two red triangles and one blue square when k=3, the circle belongs to the second class. If k=5, two red threesomes and three blue rectangles indicate the first class confidential the outside circle. Throughout the algorithm's training, a collection of learnt characteristic vectors and class tags is formed. During the critical classification stage, the unidentified class is treated as the vector in the highlighted part. To choose examples that are close to k, a variety of vectors are utilised. The novel vector detection with forecast among the K nearest neighbours is one of the most used approaches. This method's shortcoming is that its new vector prediction is based on normal conditions. As a result, if all K nearest neighbour distances are determined along with the newly categorised vectors, and the classes are inferred based on the distance values, this problem may be addressed.

### 3.4 K-Nearest Neighbor - Support Vector machine

By merging support vector machines with k-nearest neighbours, a new category is produced. One exact point is selected for each class in the technique, which is founded on SVM and KNN classification. The method establishes the radial length of the various group. Use the suitable great-plane of a support vector machine in feature interplanetary during the period phase. The support vector machine will be used in place of the k-nearest neighbour method when the test process length exceeds the predetermined threshold. The length of the experimental samples is mixed with each support vector in the KNN technique, where apiece support vector is chosen for a particular position. The k-nearest reference neighbour method is used to find the experimental modules. Computer simulations show that the combined technique not only achieves more accuracy than SVM alone but also solves the challenge of selecting the kernel value for SVM.

The equation 1 express the for KNN classification equation:

$$NewDataPointCategory = MajorityCategory(NearestNeighbors(k)) \quad (1)$$

where "MajorityCategory" represents the most common category among the k nearest neighbors, and "NearestNeighbors" represents the k training data points that are closest to the new data point.

The equation 2 represent SVM classifier can be written as follows:

$$f(x) = \text{sign}(w * x + b) \quad (2)$$

where "x" is the new data point being classified, "w" is a vector of weights that defines the orientation of the hyperplane, "b" is a bias term, and "*" represents the dot product. The function "sign" returns the sign of the result of the dot product, which determines which side of the hyperplane the data point falls on. If the result is positive, the data point is classified as belonging to one class; if the result is negative, the data point is classified as belonging to the other class.

In practice, the SVM classifier equation is often implemented using a kernel function, which allows the algorithm to handle nonlinear relationships in the data.

The kernel function can be incorporated into the equation 3 as follows:

f(x) = sign(sum(alpha_i * y_ i * K(x_ix))+b)
(3)

where "alpha_i" and "y_i" are the dual variables and class labels of the training data points, "x_i" is the ith training data point, "K" is the kernel function, and "b" is the bias term. The kernel function "K" is a mathematical function that is used to map the data points into a higher-dimensional space, allowing the SVM classifier to capture nonlinear relationships in the data.

In order to find the optimal hyperplane and coefficients in the SVM classifier equation, the algorithm must solve a optimization problem that minimizes the training error while maximizing the margin between the classes. This problem can be written as follows:

minimize(1/2 * sum(alpha_i^2))

subject to: sum(alpha_i * y_i) = 0

alpha_i >= 0

y_i * (w * x_i + b) >= 1

where "alpha_i" and "y_i" are the dual variables and class labels of the training data points, "x_i" is the ith training data point, "w" is the vector of weights, and "b" is the bias term. The optimization problem seeks to find the values of "alpha_i" and "b" that minimize the training error while maximizing the margin between the classes.

Once the optimization problem has been solved, the SVM classifier equation can be used to classify new data points by plugging in the values of "w", "b", and "x" and using the "sign" function to determine which class the data point belongs to.

## 4 Result and Discussion

The EMG signal obtained from eight electrodes, and the EMG data is shown using an eight-column medium. The Autodesk file includes variables that indicate the trial start time as well as values that match to the trial labels. The animation and Python script were then utilised for the simulation rather than any other systems. In this research, we utilised the simulation tool Autodesk 3D Max to ensure that our design would work well in practise. The 3D modelling and rendering application 3D Max is used in animation, video games, and visualisation. In this software, we utilised simulation to test the correctness of four movements. We were able to demonstrate the dependability of our 3D models fast using 3D Max toolkits and gesture methods. Though, we did initially develop a 3D model of our prosthetic robotic hand, update it depending on our work, and then preserve the bulk of the model's dimensions while allowing for calculations. We were able to get test results by connecting the MyoWare Muscle Sensor via an analogue pin to the built-in microcontroller. The muscle data collected by the electrodes from the patient is processed by an integrated CPU. The simulator's state-determining Python script variable is validated. When the gathered data surpasses the threshold value, a certain variable takes on the proper value. When we tested the accuracy of our motions on our prosthetic model, it correctly recreated four actions. When the aperture area is modified, the classification rate diverges. It is possible to establish that the expansion of the classification rate arises from an increase in the aperture with fixed aperture enhancement by analysing changes in the aperture area. The categorization rate is highest at 512 ms aperture. Although 512 ms aperture gives a higher classification rate, big aperture requires a significant amount of processing time. A fixed aperture enhancer with a 128 ms aperture size was employed in this study.

On average, the total classification rate is 96.33 percent. Figure 4 depicts the average classification rate for apeature size, anywhere the x-axis represents the apeature size and the y-axis defines percentage of classification. A horizontal line represents the mean classification rate throughout the board. The readings are shown in Table 1.

| S.No | Classification (%) | Aperture size(ms) |
|---|---|---|
| 1 | 82 | 150 |
| 2 | 84 | 230 |
| 3 | 85 | 380 |
| 4 | 91 | 500 |
| 5 | 90 | 620 |

| | | |
|---|---|---|
| 6 | 87 | 780 |
| 7 | 89 | 900 |
| 8 | 88 | 1024 |

**Table1.**Relation between classification rate percentage and aperture size

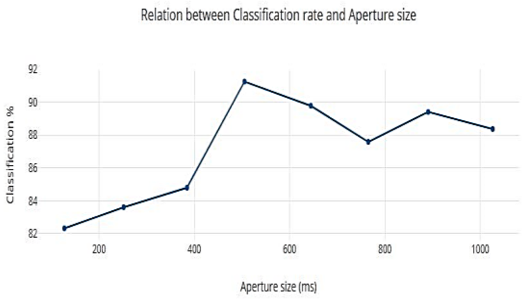


**Fig 4.** Results of the proposed method

## 5. Conclusion

Finally, for the prosthetic hand, an advanced approach called electromyography is employed, which is powered by electric signals generated by an user's own muscle system. In the AutoCAD 3-dimensional application, and artificial intelligence are utilised to design, develop, and display the EMG-based prosthetic hand control of movement. The software is originally built using a variety of feature extraction and classification approaches. This study employs three machine learning techniques and achieves classification accuracy. Variability, Sound wave Length, Sum of EMG, Zero Crossing points, Gradient Sign Changes, Motor Model, Integral Average Value, and other variables are utilised for extracting features. SVM, KNN, and a mixture of KNN and SVM procedures are cast-off for feature sorting. The SVM and KNN grouping surpasses the other two approaches in categorising four distinct hand gestures: finger-open, finger -close, spherical-grip, and finger -pinch, with an accuracy rate of 968.33 percent. The KNN + SVM algorithm combination, with the best classification rate, is undeniably superior at categorising a wide range of hand movements. In addition, we created our software simulation system using Autodesk 3D Max, a 3D modelling and rendering application. As an example of the output, consider the gesture of our created prosthetic finger model, which correctly duplicates the subject's desired movement based on EMG signal test data. This approach, which is based on MyoWare Muscle Sensor data, also gives muscles ample time to digest actions. The 3D-printed prosthetic finger with a precise finger movement control model will soon allow paraplegics to do normal chores, rendering their lives better.

## 6. Future Scope of Research

There are a number of areas where researchers and engineers are working to improve bionic arms and other prosthetic devices. Some potential areas for future work include:

Improving the control systems: Researchers are working to develop more sophisticated control systems for bionic arms, including systems that can detect and interpret more complex muscle signals and movements.

Enhancing sensory feedback: Engineers are working on ways to provide more realistic and nuanced sensory feedback to users of bionic arms, such as touch, temperature, and pressure.

Reducing the cost and complexity of implantation: Currently, the implantation of electrodes for EMG-based bionic arms is a complex and expensive process. Researchers are working on ways to make the implantation process simpler and less expensive.

Developing new materials and technologies: Researchers are exploring the use of new materials and technologies, such as advanced polymers and nanomaterials, to create more lightweight, flexible, and durable bionic arms.

Improving the cosmetic appearance of bionic arms: Many people who use bionic arms want them to look as natural as possible. Engineers are working on ways to create bionic arms that are more cosmetically appealing and that can be easily customized to match the user's skin tone and other physical characteristics.

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