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EMPLOYING EMG SENSORS IN BIONIC LIMBS BASED ON A NEW BINARY TRICK METHOD

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ABSTRACT:

Human muscles can be read by using electromyography (EMG) sensors, which are electrical signals generated by the muscles of human and animal bodies. This means it is possible to use electricity generated by muscles to control actuators/servo motors for any specific tasks. This could support a wide range of applications, especially for people with disabilities. One such application would be making bionic limbs based on servo motors. According to a study held by the K4D helpdesk report based on estimations that 15.3% of the world's population has a moderate or severe disability, this proportion is likely to increase to 18-20% in conflict-affected areas (Thompson, 2017). The goal of this study is to make bionic limbs affordable by minimizing the cost while maintaining accuracy at an acceptable rate. To achieve this goal, the study proposes a new idea for using electromyography (EMG) sensors in bionic limbs, which suggests a decrease in the number of EMG sensors to decrease the cost and power consumption. Decreasing the number of EMG sensors will result in a loss of accuracy in controlling actuators (servo motors) because usually, each sensor is responsible for activating one servo motor. In normal projects, one will need at least six EMG sensors to control six servo motors. The study will use only three EMG sensors to control/activate six servo motors depending on the *binary trick* idea suggested by this study, which is manipulating all three input signals from EMG sensors at once and then deciding which servo motor to activate by using a supervised machine learning technique such as K-nearest neighbors (kNN).

KEYWORDS: Electromyography sensor (EMG), Human computer interfacing, Bionic limbs, Machine learning, Arduino.

1. INTRODUCTION

According to the Humanitarian Needs Assessment Programme (HNAP) in Syria, there are 3.7 million or 27 percent of the total population (aged 12+) have a disability (Humanitarian Needs Assessment Programme (HNAP), 2019). This number is likely way more than the mentioned one due to the lack of accessibility in the majority of the war zone locations by humanitarian organizations, such a huge number of people with disabilities is a problem not only for the individual themselves but also for their families as well. It is also important to mention that disability has a direct impact on the economic growth of the countries too. Although these individuals are suffering from fulfilling day-to-day basic duties, this leads to more serious problems such as mental disease.

According to Cree et al., (2020) adults with disabilities report experience frequent mental distress, almost five times more than adults without disabilities. Based on these data, we do believe more efforts should be spent on helping individuals with disabilities. Starting with bionic limbs, since the 1960s many efforts have been made on making bionic limbs help people with disability (Cree et al., 2020; Parker & Scott, 1986). The majority of studies were focusing on the hand because it is one of the most important and functional parts of the human body and the part that does a lot of complex tasks. Most methods are based on reading the electrical signal (amplitude) generated by an EMG sensor to move or control one of the servos that are attached to Degrees of Freedom (DOF) (Farina et al., 2014). One of the major problems for Myoelectric (ME) prostheses not being used by people who need them, is due to their high cost as shown in Table I (Williams, 2021).

2. EMG SENSOR AND RELATED WORK

surface electromyography (EMG), lately has gained a lot of popularity among researchers, because EMG signal can provide information about a person's desire to move skilfully, therefore, it can easily be integrated with robotic control commands. EMG used placed on the skin surface by using electrodes, and can encode information generated by the human brain (Wallroth et al., 2018). The skin can either be dry or wet to interface it with electrodes, when the skin is wet gel is required on between electrode and the skin to reduce the electric resistant and improve the stability of electrodes (Laferriere et al., 2011). While for the dry skin no gel is required to interface it with the electrode, up to now, many researchers have investigated EMG sensors and applied it to control robotic interface, these investigations can be divided into three categories: controlling prosthetic arms, remotely operated robots mainly used in medical surgeries, and the application of orthoses. (Bitzer & Van Der Smagt, 2006) controlled a four-fingered robot hand using EMG sensor inputs from 10 forearm muscles, according to (Cimolato et al., 2022) the results indicates that there is a lack of quantitative and standardized measurements among the researchers that work on EMG based bionic limbs which hinders the possibility to analyze and compare the performances of different EMG-driven controllers.

It is important to mention that all EMG based prosthetics need to consume a lot of muscle power (squeezing muscle) to activate the prosthetic limb, which consequently leads to the majority of amputees abandoning the prosthetic limbs (Cordella et al., 2016).

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One of the key factors of prosthetic rejection is comfort, in which none of the commercial prosthetic arms succeeded in making a long-term comfortable prosthetic arm (Biddiss & Chau, 2007), according to (Gailey et al., 2010; Roffman et al., 2014; Walden, 2017), the major reason that ultimately leads to abandonment of the device is poor mobility. Additionally, amputees continue using their prosthetics will exposure to significant risks of acquiring a number of cardiovascular and neuromusculoskeletal diseases. (Burke et al., 1978; Gailey et al., 2008; Kušljugić et al., 2006; Naschitz & Lenger, 2008) the EMG sensors to control servo motors as DOFs for hand. Usually, the number of EMG sensors should be at least equal to or more than the servo motors number to increase accuracy, DOF and control as many servos as possible. However, by increasing the number of EMG sensors the cost, power consumption, and complexity also increase proportionally, since each EMG sensor is responsible for activating one of the servo motors. This study suggests decreasing the number of EMG sensors for the purpose of decreasing the cost and complexity, it decreases accuracy as well. To solve the issues related to the accuracy a pattern recognition (PR) technique will be considered in this paper as it has been used by (Lee & Saridis, 1984; Li et al., 2019; Williams, 2021). This article will provide a new concept for bionic limbs based on EMG sensors to decrease building cost by decreasing the number of EMG sensors and Leaving DOFs as it is. The evaluation of the obtained results will be compared with state of art results based on accuracy, responsiveness in milliseconds (ms), and the number of classes. As for testing purposes, six DOFs will be controlled via six servos by using only three EMG sensors and applying a new idea called *binary trick* by manipulating all three signals generated by EMG sensors at once and then deciding which servo motor will activate/fire by using machine learning techniques.

The rest of the paper is organized as: Section one technical details about hardware are discussed. Section II explains the hardware, and software architecture of the entire system, as well as the basic pattern recognition (PR) algorithm that runs on the embedded system. Section III details the EMG PR experiment with real-time performance measurements for several classifiers and features. Section IV summarizes the findings of the experiment.

TABLE I. COST OF SOME EMG BASED BIONIC LIMBS SYSTEM

Bionic Hand	Price Category (USD)	Current Availability
Ability Hand	\$20,000 to \$30,000	USA
Adam's Hand	\$30,000 to \$40,0001	Italy Q1 2022, USA, Germany, France, and Spain later in 2022
Atom Touch	More than \$50,0002	USA (launch date 2024)
Bebionic Hand	\$30,000 to \$40,000	Global
BrainRobotics Hand	\$20,000 to \$30,000	USA (launch date 2021/2022)
Grippy	\$10,000 to \$20,0003	India
Hero Arm	\$10,000 to \$20,000	USA, UK, Europe, Australia, New Zealand
i-Limb Access	\$40,000 to \$50,000	Global
i-Limb Ultra & Quantum	More than \$50,000	Global

3. SYSTEM CONSTRUCTION

The system consists of three main parts, three EMG sensors each of them has three channels, 6 servo motors, one unit of Arduino Uno chip, and two units of 9v batteries, and machine learning techniques such as SVM (Support Vector Machine) and KNN (K-nearest neighbor) to make the right decisions and control which servo should operate once an EMG sensor amplifies. Because the EMG signals have varying voltage thresholds, it results in a lot of noise while acquiring signal data. To solve this issue, some prepossessing steps are required before applying any classification method. General diagram of the system is shown in Figure 1

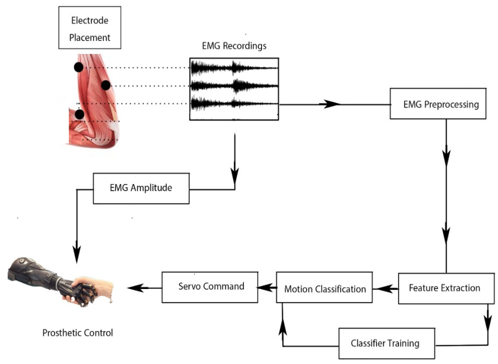

Figure 1. Schematic diagram of bionic limbs based on EMG sensor

3.1 Electromyography (EMG)

EMG is a technique for evaluating and recording the electrical activity produced by skeletal muscles, (Paoletti et al., 2020; Park & Lee, 1998). The generated amplitude from muscle activity for surface EMG is ranged between 0 to 10mV (milliVolt) (Robertson et al., 2013). When muscle cells are electrically or neurologically activated, electromyography monitors the electric potential generated by these cells (Shetty et al., 2010). The signals can be studied to look for abnormalities, levels of activation, or recruitment orders, as well as to look at the biomechanics of human or animal movement. Many research emphasizes that the location of EMG sensors on human muscle/skin has a huge impact on output signal characteristics (De Luca, 1997; Elfving et al., 2002; Farina et al., 2002; Hermens et al., 2000; Jensen et al., 1996; Kleine et al., 2001), although it is known that one or more sensors are being used to read each muscle's move, which means for each system a bunch of EMG sensors is required to obtain accurate results (Falla et al., 2002; Farina et al., 2001; Jensen et al., 1996). There are two types of EMG sensors, *surface EMG* and *intramuscular EMG*. In this study, only three surface EMG sensors have been used to control five DoFs (degrees of freedom) for bionic limbs.

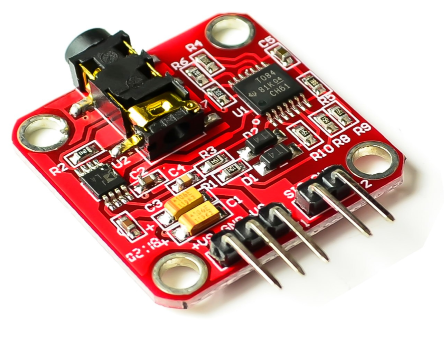

Figure 2. EMG sensor unit

The reason for choosing surface EMG sensors is that they are more affordable and easier to wear, however, intramuscular EMG is more accurate. A raw sample of muscle activity from the surface EMG sensor can be seen in Figure 2., which is generated by the Arduino analogue data reader window. The sensor type that has been used in this study contains a small, printed circuit board (PCB) with three electrodes for the skin surface; one of the electrodes is placed on a bony feature as a ground reference point; the other two electrodes for voltage measuring of any potential within muscles.

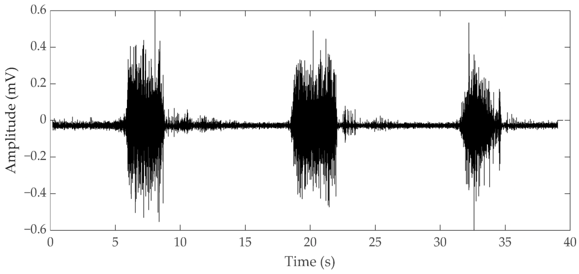

Figure 3. EMG sensor unit

3.2 Pre-processing

After reading the raw Data from the EMG signal, the first step would be pre-processing, since human muscle can generate many unwanted muscle activities and various noise components, such as powerline interference (PLI), baseline wandering (BW), and white Gaussian noise, are erratically affecting the surface of EMG signal. These noises have a direct impact on the EMG processing efficiency, accuracy, and reliability of the system. To solve some of these problems we decided to use a Hampel filter, which can easily detect and remove outliers in the input signal. The Hampel identifier is a statistical version of the three-sigma rule that is robust to outliers (Allen, 2009). Figure 3. demonstrates the performance of the Hampel identifier algorithm. The filter is applied by using the SKTIME framework, by setting the sliding window step size to 10 and leaving sigma value three as default. The resulting signal is way more robust for processing compared to the original signal, furthermore, it can be seen the large outliers have been removed. To be more precise about the filtering process, the more filtering techniques we apply, or use, the better results we could get, but it will negatively affect the performance. The study believes that the choice of the Hample filter is a good balance between performance and accuracy.

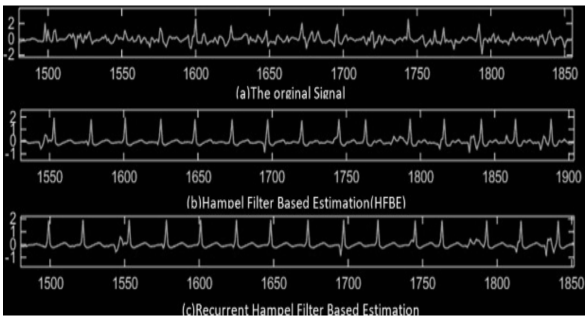

Figure 4. Applying Hample filter on raw EMG signal

3.3 Classification method

The major step in bionic limb systems is the input signal generated by the EMG sensor, it is represented as a Feature vector in the feature extraction step, which is forwarded as an input to the classifier. Since there is a lot of randomness and noise level generated by unwanted muscle movement, it is highly affecting the EMG signal shape, for that reason, it cannot be forwarded directly into the classifier, the classification method and step depends on the EMG signal to perform a good accuracy (Langzam et al., 2007; Zardoshti-Kermani et al., 1995). In the presented study, the KNN (K-Nearest Neighbor) classification technique has been used by using a python programming language in collaborator with google to perform the classification activity. Many researchers applied different classification methods and their performance is evaluated as shown in table 2. This study preferred the k-nearest neighbors (KNN) algorithm as the classifier to perform EMG signal recognition and decide which actuator (servo motor) to activate. The reason behind choosing the KNN algorithm is due to its light performance for performing calculations in real-time, ease of implementation, and fast retraining. The downside of using KNN, it may lead to inaccurate results and consumes a lot of space in Random Access Memory (RAM) by storing all the training data for each time making a prediction. The KNN method is based on two phases: the first one is the learning phase, in EMG signal data which is generated in real-time and collected to perform the training process, while the second phase is the classification phase, the new input data is compared with all the training data and then decided to what class it belongs with the most-similar training data. This study got benefit of (Shi et al., 2018) research of four k-values: 5, 7, 9, and 11 were tested in this study k-value with 11 performing most accurately among other k-values.

4. RESULTS AND DISCUSSION

The majority of studies which work in the field of bionic limbs tend to increase the number of EMG sensors to increase the accuracy and degrees of freedom (DoFs). However, by doing so they intend to increase the cost and power consumption of the system. In this study we used a trick namely, that is called a **binary trick** to decrease the number of EMG sensors and yet be able to control more servos than the actual number of EMG sensors. In a binary system, when you have two digits, four possible values can be generated; and for three digits eight values can be generated, based on this concept we build up our system, by manipulating three signal values read by an EMG sensor at once and then decide which actuator should fire, the study knew that this will decrease the accuracy of the system, and it gets even more complex for the system when a user decides to move multiple fingers at once, to solve this issue even partially some machine learning techniques have been tested and used to improve the result as much as possible. However, the main goal was to make a system with fewer EMG sensors than usual and get acceptable results to open a door for further study to improve the accuracy issue.

TABLE II. EMG BASED BIONIC SYSTEM COMPARISON

Author	Method	Time (ms)	Classes	Accuracy %
(Zhou et al., 2010)	Linear discriminant analysis (LDA)	Not available	11	81
(Oskoei & Hu, 2008)	Support vector machine (SVM)	200	6	95
(Karlik et al., 2003)	Fuzzy K-nearest neighbor (FKNN)	80	6	98
(Tenore et al., 2008)	Multilayer perceptron (MLP)	200	12	>90
Proposed system	**K-nearest neighbor (KNN)**	**120**	**6**	**83**

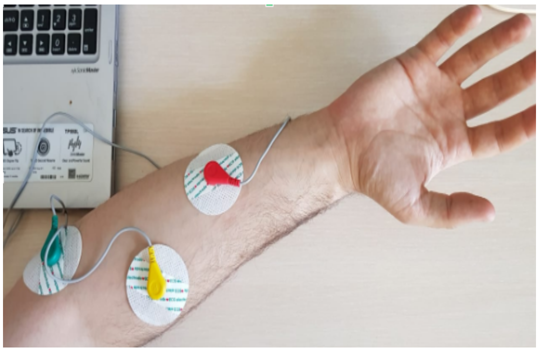

Figure 5. Single EMG electrodes

5. CONCLUSION

Technology-driven bionic limbs are gaining popularity because they perform functions similar to human limbs. However, one of the major problems with such technologies is their high cost. As shown in Table 1, since the majority of people who need such technology is from poor or war zone countries, it is nearly impossible for them to afford such technology for its price tag, the goal behind this study was an attempt to decrease the cost of bionic limbs by decreasing the number of EMG sensors and maintaining accuracy at an acceptable rate. For that purpose, the study introduced a new idea called the binary trick method. By applying this trick, the system was able to control up to six actuators (servo motors) by using only three EMG sensors alongside some classification methods such as k-nearest neighbor (KNN). However, the classification step is suffering to decide which finger should move once the user attempts to move more than one finger simultaneously. Furthermore, the system achieved less accuracy compared to previous research as shown in table 2. The bright side of the study was successfully approving that it is possible to control a number of actuators (servos) by using a fewer number of EMG sensors than all other previous research. With the help of the KNN algorithm for classification purposes, the study also believes that the accuracy issue can be solved by applying more experiments on machine learning based algorithms, filtration methods, and improving the EMG sample collection methods.

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