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Applying Biosensors' Electromyography Signals through an Artificial Neural Network to Control a Small Unmanned Aerial Vehicle

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***Abstract*—**This work describes a system that uses electromyography (EMG) signals obtained from muscle sensors and an Artificial Neural Network (ANN) for signal classification and pattern recognition that is used to control a small unmanned aerial vehicle using specific arm movements. The main objective of this endeavor is the development of an intelligent interface that allows the user to control the flight of a drone beyond direct manual control. The sensor used were the MyoWare Muscle sensor which contains two EMG electrodes used to collect signals from the posterior (extensor) and anterior (flexor) forearm, and the bicep. The collection of the raw signals from each sensor was performed using an Arduino Uno. Data processing algorithms were developed with the purpose of classifying the signals generated by the arm's muscles when performing specific movements, namely: flexing, resting, and motion of the arm. With these arm motions roll control of the drone was achieved. MATLAB software was utilized to condition the signals and prepare them for the classification. To generate the input vector for the ANN and perform the classification, the root mean square and the standard deviation were processed for the signals from each electrode. The neuromuscular information was trained using an ANN with a single 10 neurons hidden layer to categorize the four targets. The result of the classification shows that an accuracy of 97.5% was obtained. Afterwards, classification results are used to generate the appropriate control signals from the computer to the drone through a Wi-Fi network connection. These procedures were successfully tested, where the drone responded successfully in real time to the commanded inputs.

***Keywords*—**Biosensors, electromyography, Artificial Neural Network, Arduino, drone flight control, machine learning.

I. INTRODUCTION

INTELLIGENT control of vehicles (drones, cars, robots, etc.) is required for many applications. In particular, the use of EMG devices used to collect neuromuscular-activated signals from human subjects and their use to generate commands to control different types of vehicles, ground and aerial, is becoming an emerging filed. Moreover, with the exponentially growing number of internet-connected devices, the need to develop a more natural human-machine interface arises. This paper discusses the development of an arm-movement based control system as a means of controlling a small-unmanned aircraft system (sUAS).

Reconnaissance unmanned aerial vehicles were first deployed on a large scale during the Vietnam War for military purposes because they did not expose the life of pilots in combat zones [1]. Nowadays, drones have become very common in civilian and commercial applications and anyone can have access to drones and use them for multiple purposes in different fields such as surveillance and security, package transportation, and photography.

Drones are usually controlled using a joystick, smartphones or a tablet. However, using any of these devices has the problem that the hands are used to hold the device and this can be problematic for some users, especially for people with disabilities, which many times cannot have total control of their hands and arm movements.

The main goal of this project is to present an alternative to drone control using surface electromyography (sEMG) signals which could help anyone, even people who are disabled, to take advantages of utilizing drones for multiple purposes. EMG is the study of muscle electrical signals. It has been 30 years since sEMG signals have been proposed to detect the hand motion of human subjects with applications to the control of prosthetic hands [2]. Classification methods to discriminate among different arm and finger movements have been proposed by many researchers [3]-[5].

For EMG signals there are two ways to collect the data: invasive electrodes and non-invasive electrodes. The signal that is detected by the electrodes is a composite of the muscle action potentials directly under the skin. In order to obtain a response from one muscle specifically, an invasive electrode must be inserted under the skin into the muscle. The non-invasive electrode or better known as sEMG is a collection of muscle action potentials for a single motor unit action potential (MUAP). A simple equation for muscle action potential detection is shown in (1):

$$x(n) = \sum_{r=0}^{N-1} h(r)e(n-r) + w(n) \qquad (1)$$

In (1), the output x(n) is the modeled EMG signal, *e(n)* is the

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point processed, *h(r)* is the MUAP, *w(n)* is the zero mean additive white Gaussian noise and *N* is the number of motor units firing [2]. Once the signal is acquired it must be amplified, noise must be removed, and unwanted motion signals must be eliminated. In order to obtain cleaner signals, additional hardware and computing units that can execute signal processing are used. Most applications are concerned only with the amplitude of the signal. The *x(n)* signal can be rectified and averaged to achieve this.

EMG signals can be measured using sEMG probes which measure the muscle action potentials. These data can then be used to detect movement, fatigue, and muscle dystrophy [2]. EMG signals are widely used today for human computer interaction and Evolvable Hardware chips improvement. In order to be used for computer interfacing, the signals must be measured, denoised, amplified, and then classified. It is important to filter the EMG signals in order to reduce the signal to noise ratio (SNR) along with other factors to obtain reliable clean signals. After filtering and amplification, a feature extraction stage must be implemented. Then, signal processing algorithms are used to classify and identify the type of muscle motion that was performed. Machine learning is often used in order to best classify the EMG signals [3], [4].

II. Methods

A. EMG Sensors

In this work, MyoWare Muscle Sensors [6] were used in order to collect raw sEMG signal from human subjects. The MyoWare sensors have an input impedance of 110 GΩ, and are powered by two standard CR2032 coin cell batteries connected in parallel for extended capacity at a nominal 3.0 V. Connecting the MyoWare Muscle Sensor to battery power allows for a cleaner signal while eliminating the possibility of creating a dangerous current path to the power grid. Each MyoWare sensor has two muscle electrodes that are placed in the middle of the muscle body and should be aligned with the orientation of the muscle fibers. It has one reference electrode that is placed on a bony or nonadjacent muscular part near the targeted muscle. The MyoWare muscle sensors were placed to collect data from the posterior (extensor) and anterior (flexor) forearm, as well as data from the bicep (Fig. 1).

The collected data (raw voltages) from each electrode were processed by an Arduino microcontroller and signal processing algorithms were developed with the purpose of interpreting the voltage signals given when performing the arm movements: flexing the arm and squeezing the hand at the same time (flexing-squeezing), and relaxing the arm. Each electrode collected data at a sample rate of 4 Hz over a 2-second period for the duration of one minute, per assessment. During each 2-second interval the movements were alternating between a relaxing reference class, and an active motion class flexing-squeezing. These movements of the arm were used to control the motion of the drone. The flexing-squeezing gesture was used to move the drone laterally to the left, and the relaxing gesture was used to move the drone laterally to the right. Moving the arm up, commanded the drone to take-off and hover at 1 m level from the floor. Moving the arm laterally right-to-left commanded the drone to land.

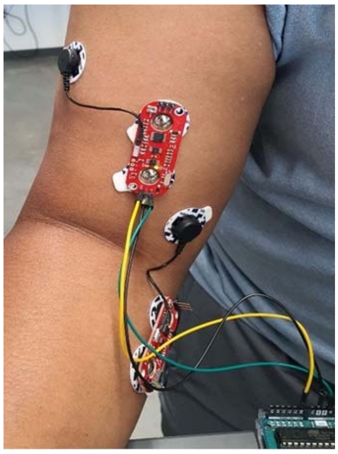

Fig. 1 MyoWare Muscle Sensors placed on forearm and bicep

B. Signal Processing and Feature Extraction

The raw EMG signals were sent to the Arduino where the signals were captured and rectified. Then the processed signals were sent to a laptop computer to be filtered to reduce noise (Fig. 2). This stage was performed using MATLAB using a high pass filter with a cutoff frequency of 20 Hz, to reduce low-frequency noise such as movement artifacts [7]. After the signal processing stage, features were extracted from the EMG signals. For the feature extraction stage, the signals from each electrode were trimmed to a length of one second, then the root mean square (RMS), and the average value rectifier (AVR) were computed. A database with four different arm movements (flexing-squeezing, relaxing, arm up, and arm laterally right-to-left) was created. Once the feature extraction was completed, the data were used to train an ANN that classified the arm movement.

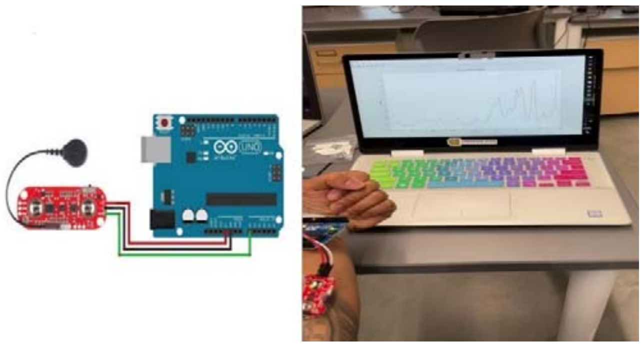

Fig. 2 The MyoWare muscle sensors interfacing with the Arduino Uno and then communicating with a laptop computer to perform the signal processing and feature extraction

C. ANN Architecture

ANNs are inspired by the human brain, mimicking the way that biological neurons signal to one another [8], [9]. The ANN was used to detect patterns in our data and differentiate the arm motions from each other. An input matrix containing the processed data was entered to the network and it returned an output matrix that indicated which arm movement was being performed by the human subject. The dataset in this work consisted of 80 hand motions from one human subject. There were four classes selected: Class 1 – Relax position for roll control (move right); Class 2 – Flexing-squeezing arm motion for roll control (move left); Class 3 – Arm-up movement (take-off); and Class 4 – Lateral-arm movement (landing).

The ANN consisted of 8 input nodes, corresponding to 4 electrodes (two sensors), and each electrode provided data in the form of RMS and AVG values. The output matrix (target classes) consisted of a column array 4x80. The ANN architecture used in this project was a feed-forward back-propagation network with multi-layer perceptron, developed using the scaled conjugate gradient training function with 8 neurons in the input layer, 4 neurons in the output layer, and one hidden layer. The hidden and output layer used tan-sigmoid activation functions. The number of hidden neurons were initially set between the number of input and output neurons and then adjusted for accuracy based on training results [3]. It was found that the network performed best with 10 neurons in the hidden layer. From the signals in the database, 70% were used for training, 15% for validation, and 15% for testing.

Currently in our project we have trained the ANN to classify four arm movements: flexing-squeezing, the relax position, arm-up, and lateral-arm motion. The flexing and relax movements performed the roll control in the drone, this is, it moved the drone horizontally to the left or to the right. Each time a command was performed the drone moved horizontally in intervals of 0.2 meters. The arm-up motion was used for take off, and an arm lateral movement was used to command the drone to land.

D. The DJI Ryze Tello Drone

The sUAS received control commands via Wi-Fi. These commands were generated from the output of the ANN classification system. The sUAS used in this project was a DJI Ryze Tello Drone Model TLW004 (Fig. 3). Its dimensions are 9.6 x 9.1 x 4.1 cm, it weighs 81.6 g which makes it easy to control and is very suitable to be tested indoors, its battery provides 13 min of flight time.

Fig. 3 The DJI Ryze Tello Drone

The output of the ANN classifier was used to control the drone in real time. The two EMG sensors were placed on the human subject's arm (Fig. 1) and the subject first performed the take-off motion, followed by a series of flexing and relaxing arm motions. The output of the ANN classifier was sent via Wi-Fi to the drone to control its roll, allowing it to move horizontally (right and left). Results demonstrated that the drone was able to be controlled with high accuracy in real time. Fig. 4 shows the flowchart of the drone commands.

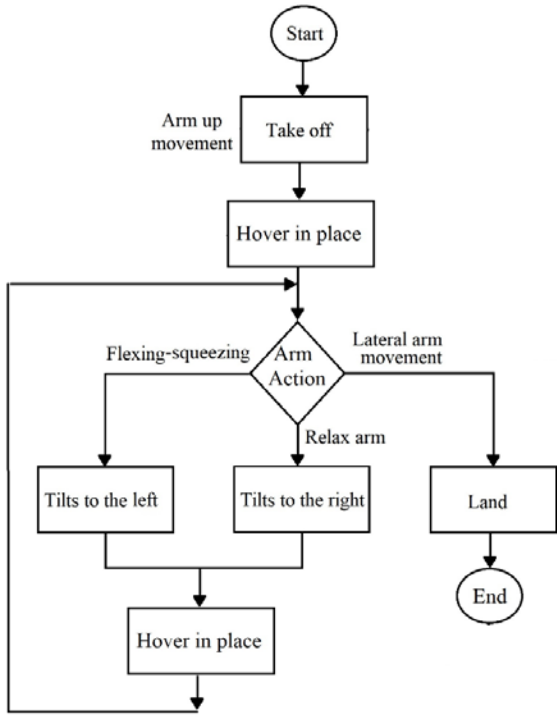

Fig. 4 Flowchart of the drone commands

III. Results

The main objective of this project was to create a type of wearable control module that can be used for directly command a small unmanned aerial system. EMG sensors were selected to collect data from a human subject performing arm motions. In this project we were able to successfully control in real time the DJI Ryze Tello drone using arm motions. Two simple arm motions, flexing and relaxing, controlled the roll in the drone moving the drone horizontally to the right and to the left, in intervals of 0.2 meters. An arm-up movement was used to command take off, and a lateral-arm motion was used to command the drone to land.

The performance of the ANN is shown in the confusion matrix in Fig. 5. This matrix shows the results of testing 80 independent hand motion signals taken from one of the volunteers. This matrix shows that the arm movements used for the commands take off and land were very distinctive providing a 100% accuracy. Meanwhile, the arm movements used to control the roll of the drone yielded a 90% accuracy. The overall accuracy of the control system was 97.5%.

Results of this type of systems may have uses in commercial, military, and recreational applications. EMG control is not limited to drones, as it was performed in this project, EMG control can be employed in broad variety of electronic devices.

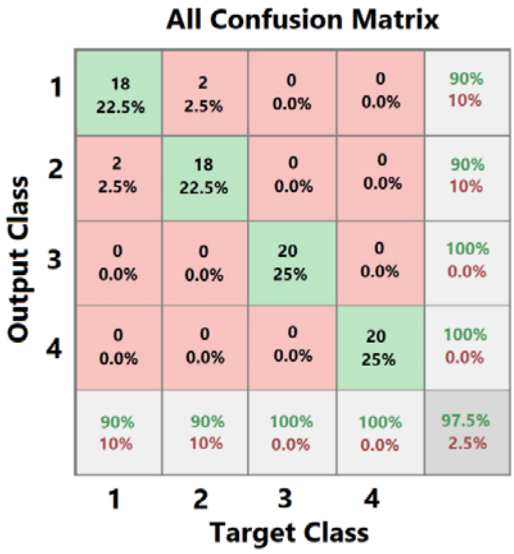

Fig. 5 Results of training the ANN

IV. Conclusions

The implemented system performed well in real time with an overall accuracy of 95.7%. However, for this system to have more practical applications, more control motions need to be added. Besides the roll control, the current system is being expanded to include yaw, pitch, and throttle control.

Currently, this work uses MATLAB software for the training and implementation of the ANN classifier; however, to make this type of systems more efficient and have faster response, other programming languages such as Python should be used.

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