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DRONE CONTROL USING BCI TECHNOLOGY

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An honors Thesis submitted in partial fulfillment of the requirements for Honors in Electrical Engineering

By

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Under the mentorship of Dr. Rocio Alba-Flores

ABSTRACT

A drone, also known as an unmanned aerial vehicle (UAV), is a type of aircraft that is operated remotely or autonomously. The utilization of drones increased because it is now possible to use them to perform tasks that would be too complicated for human beings to do. Electroencephalograms (EEG) are generated by the electrical activity of the brain and can be measured by placing electrodes on the scalp. The idea of controlling drones using EEG signals refers to the use of EEG technology to control the movement of a drone. EEG signals are used to determine the user's intention and translate that into commands that are sent to the drone.For this project, we developed and tested a system that has the purpose to control a drone using a headband that detects EEG signals from the drone’s pilot when he/she performs facial gestures. A commercial EEG headband will be used to record the EEG signals generated when three facial gestures are performed: raise eyebrows, hard blink, and look left. The headband has three electrodes in the form of small metal disks that allow three frontal cortex measurements. For this experiment, the recordings will be taken from three different people and the EEG signals recorded from them will be analyzed and recorded using the OpenBCI GUI software. The data recorded will be transferred to MATLAB software. Then the data will go through a feature extraction process, to design an Artificial Neural Network (ANN). After that, the Artificial Neural Network will be trained to classify the facial gesture selected for the experiment and once its training is completed the Neural network will be converted into a function that will be sent to MATLAB for the purpose to send commands DJI Tello drone based on the classification analysis performed by the Neural Network created.

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CONTENT:

INTRODUCTION:

Drones have been around for more than two decades, but their roots date back to World War I when both the U.S. and France worked on developing automatic, unmanned airplanes [1]. for the last few years, the popularity of drones has improved significantly due to the usage expansion across industries, and global awareness. From technically manning sensitive military areas to luring hobbyists throughout the world, drone technology has developed and prospered governments have come to realize that drones have multiple useful features, which include: aerial photography for journalism and film, express shipping and delivery, gathering information or supplying essentials for disaster management, thermal sensor drones for search and rescue operations, geographic mapping of inaccessible terrain and locations, building safety inspections, precision crop monitoring, unmanned cargo transport, law enforcement and border control surveillance, storm tracking, and forecasting hurricanes and tornadoes

The current state of drone control technology has advanced significantly in recent years, with improvements in both hardware and software. However, there are still several limitations and challenges that exist controlling these devices can be challenging, especially in complex or hazardous environments. Traditional joystick controls require significant training and skill and can be difficult to use in situations that require precise and responsive maneuvers. In addition, joystick controls may not be intuitive or responsive enough for certain applications, such as precision agriculture or search and rescue operations.

BCI has always been a fascinating domain for researchers. The Brain-Computer Interface (BCI) system has directly connected the human brain and the outside environment. The BCI is a realtime brain-machine interface that interacts with external parameters. Recently, it has become a charming area of scientific inquiry and has become a possible means of proving a direct connection between the brain and technology such as drones.

In this thesis, we will examine the potential of BCI technology to improve drone control and make it more intuitive and efficient for users. EEG signals from three subjects were recorded and analyzed using the OpenBCI headband kit. This headset uses electrodes to read the electric field potentials generated from the user when he/she performs neurological activities (e.g. focusing in a specific thought or performing facial gestures) and displays the signals as EEG signals. The recorded signals are displayed via the OpenBCI GUI software, allowing the user to visualize and analyze the data.

In analyzing the data, different statistical methods were used to extract the desired features. The statistical analysis was performed using MATLAB tools. Once the feature extraction was completed, the data were used for the training and testing of an Artificial Neural Network (ANN) that was able to classify the neurological activity generated by the user. After the neural network has been trained and tested to recognize the different gestures, the output of the ANN is used to control a DJI Tello drone. The DJI Ryze Tello is a small drone with an onboard nose-mounted camera capable of capturing 5MP photos and streaming 720p HD video. It is a lightweight and affordable quadcopter, perfect for flying indoors ideally suited to newcomers to the hobby [2].

Three different drone commands were selected and related directly to three different facial gestures. This paper is organized as follows: the method section will explain every step followed for the completion of the project such as how the EEG headband was used to collect the EEG data, the data collection methods, the feature extraction steps, and how the artificial neural network was created. The results section will present the results we got from the methods we used for this project, and then there will be a discussion and conclusion section to give the conclusions we made based on the results we got during the experiment.

LITTERATURE REVIEW:

Brain-computer interface (BCI) technology has recently been utilized to control various types of drones. This literature review provides an overview of the current research on drone control using BCI technology, including the methods used, the results obtained, and the potential applications of this technology.

In a study, Choi et al. (2015) used a similar approach to control a quadcopter drone using a motor imagery based BCI system. The participants in this study were able to control the drone's altitude and direction using their brain signals, and the results showed that the BCI system was effective in controlling the drone in both indoor and outdoor environments [3].

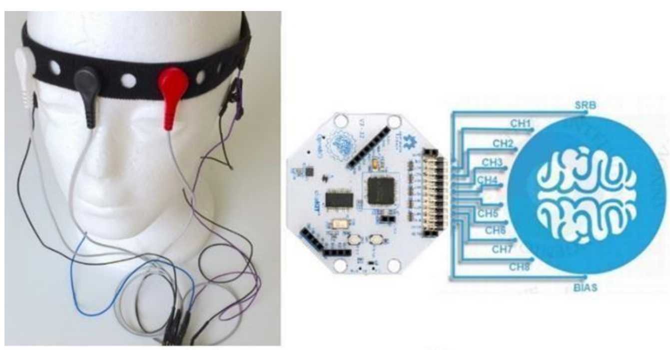
Another study by Wu et al. (2014) in which he proposed a new brain-computer interface (BCI) scheme for wheelchair control that combines two types of mental tasks (motor imagery and steady-state visual evoked potential) to provide multi-degree control and parallel command implementation. A training paradigm with visual and auditory cues and feedback is designed to effectively teach users hybrid mental strategies. The authors also propose an algorithm based on the entropy of classification probabilities to detect intentional control states and ensure accurate and quick generation of multi-degree control commands. The experiment results demonstrate the efficiency and flexibility of the proposed hybrid BCI for wheelchair control in the real-world [4].

Overall, the studies reviewed suggest that BCI technology can be used to effectively control drones in a variety of environments. However, the accuracy and reliability of the control depend on the quality of the signals recorded and the complexity of the control task. Further research is needed to explore the potential applications of this technology in areas such as search and rescue, surveillance, and precision agriculture.

METHODS:

I- Materials

To collect the data used for this project we used an OpenBCI headband kit. The kit comes with a headband (fig1a), and 12 flat EEG snap dry electrodes which allow frontal cortex measurements at F7, AF7, Fp1, Fpz, Fp2, AF8, and F8 via the three included lead wires with flat EEG snap electrodes, and an 8-channel biosensing board (fig 1b) used to capture the EEG signals detected by the electrodes. For the purpose of our research, three flat electrodes were placed at Fp1, Fpz, and Fp2 (fig 1c) and two ear clips with replacement electrodes were used and connected to the cyton board for our data collection.



(a) *(b)*

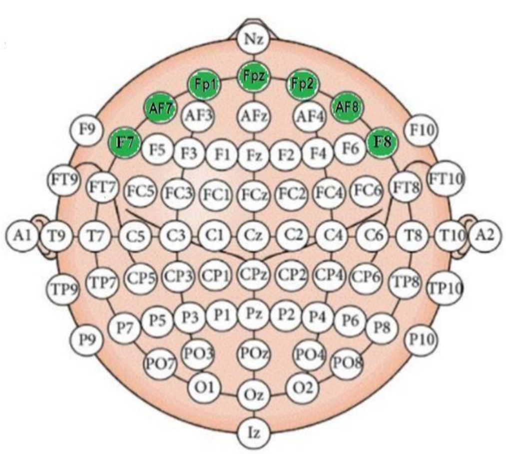


Figure 1a). OpenBCI EEG Headband, 1b) The 10- 20 internationally accepted EEG node placement system [3], 1c) Cyton board (8-channel biosensing board)[4]

II- **Data collection and feature extraction**

The EEG signals generated when the selected facial and head gestures were performed were recorded using the OpenBCI GUI software. For this research, two facial gestures and one head movement such as: raising eyebrows, looking right, and hard blink were selected. The data was acquired from the electrodes and was processed using the OpenBCI Cyton biosensing board and we were able to display and analyze it using the OpenBCI GUI software. The software displays the signals in different formats: it can be viewed as a time series (fig 2a,2b,2c) that shows the signals as they are collected in real-time, as a times series plot of amplitude in microvolts vs frequency in hertz, which parts of the brain are experiencing the most activity.. In this project, the data was collected at a rate of 225 samples per second and sent to MATLAB as a table of values.

Collecting the facial gestures consisted of the subject repeating one gesture for 6.3 s, resting for 5 s, then performing the second gesture, resting for 5 sec, and then performing the third gesture. Each session was separated by a 60 s rest period. We had 45 recordings composed of 15 sessions for each gesture with each participant being recorded doing each gesture.

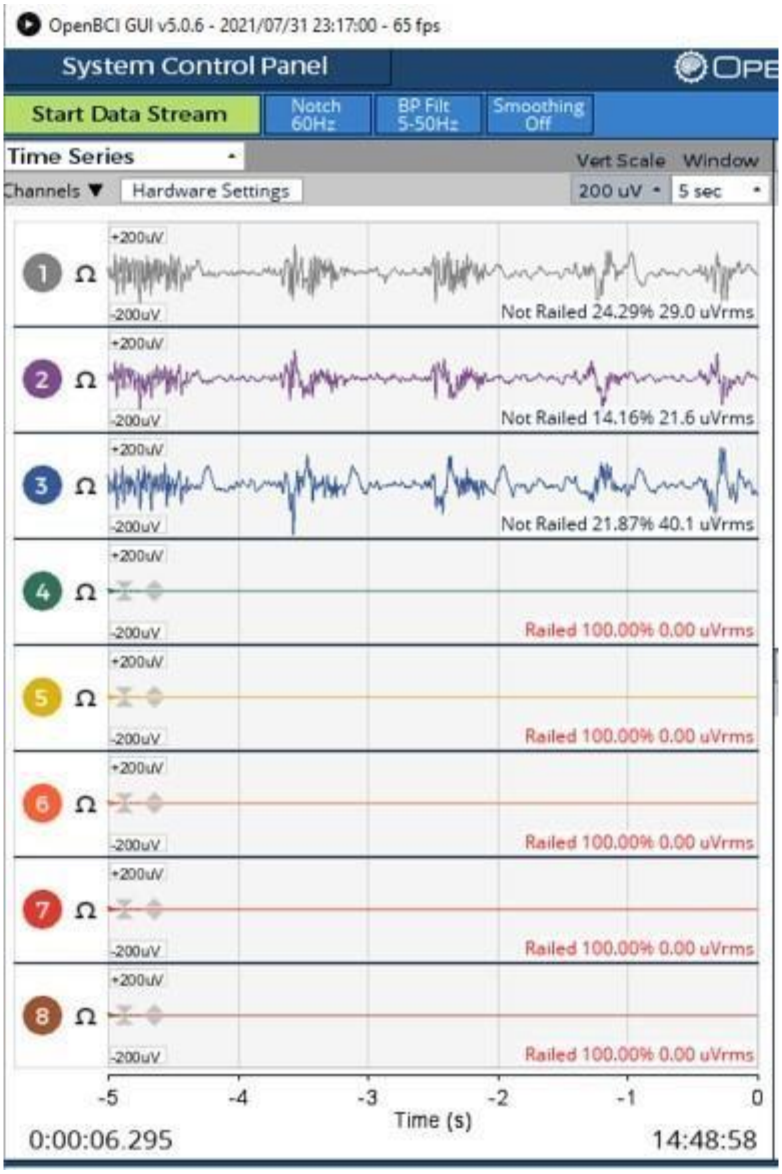


Fig2 a: Time series plot generated in OpenBCI software when performing eyeraise.

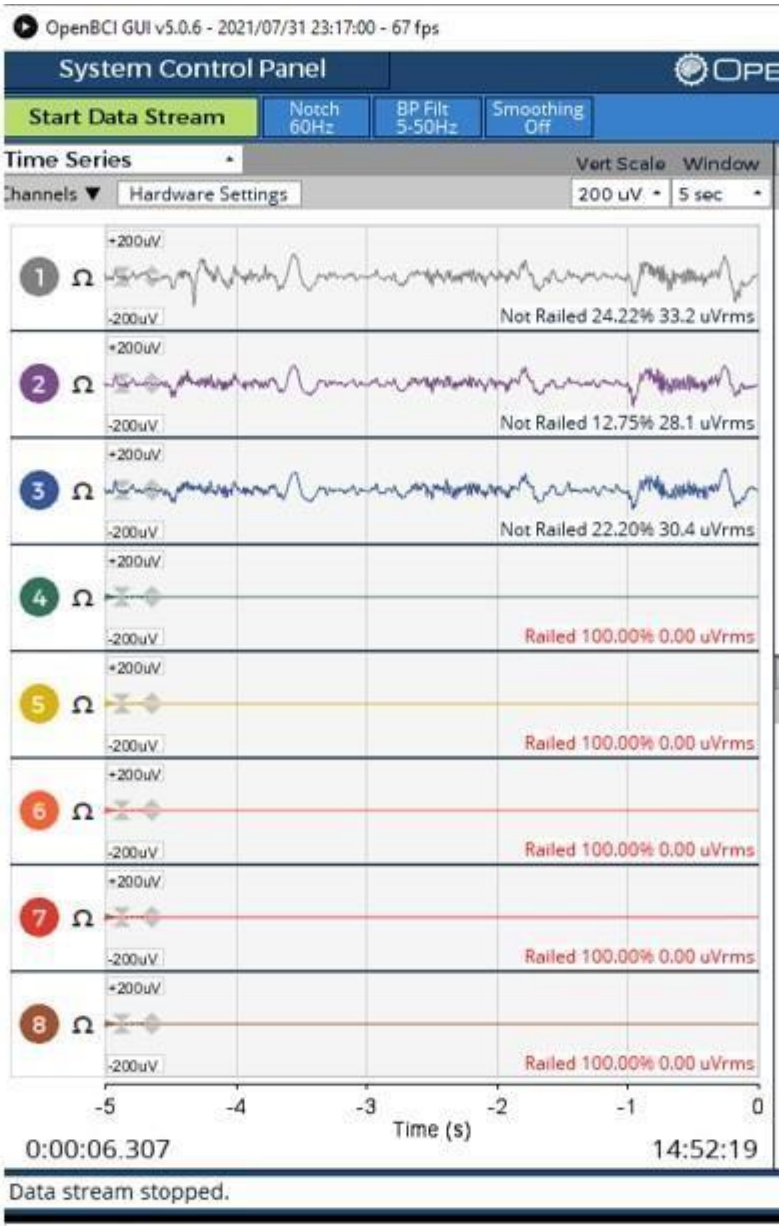


Fig 2b: Times series plot generated in OpenBCI software when performing Hard blink.

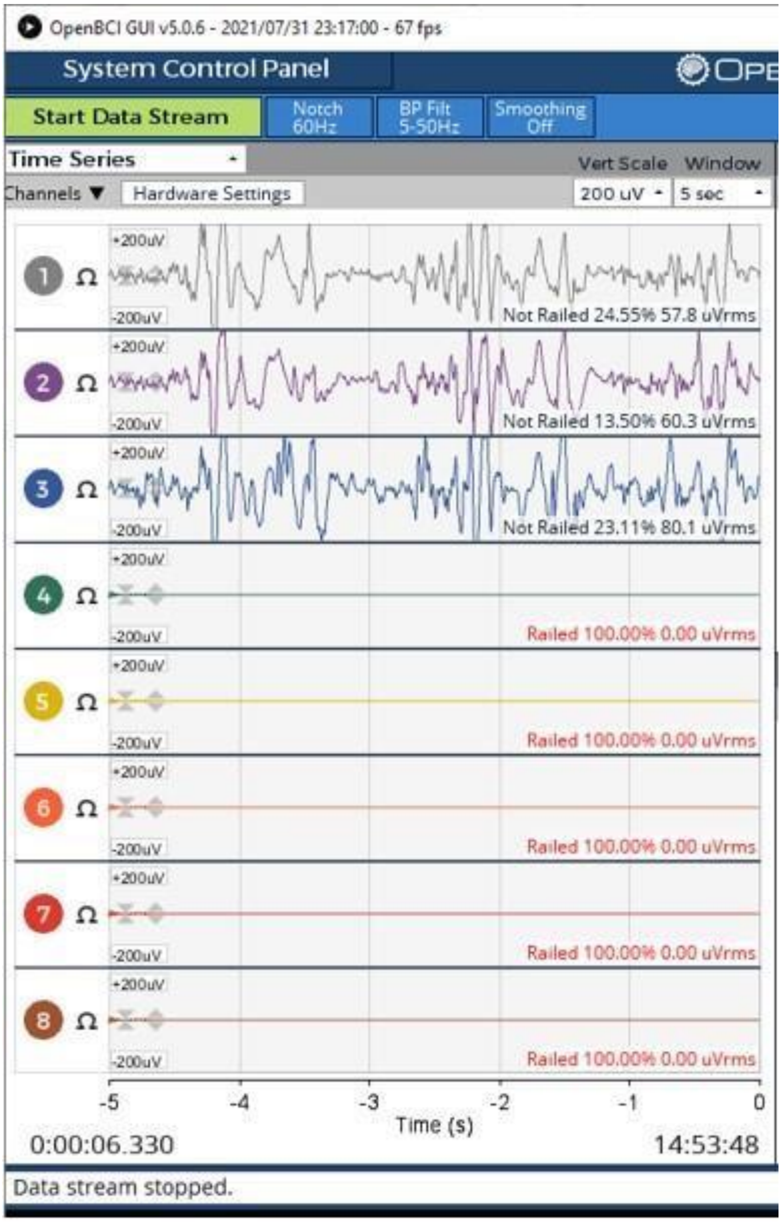


Fig 2c : Time series plot generated when performing lookright

The collected data (voltage values from electrodes) were saved in a table. This table was then imported into MATLAB, and the feature extraction process was performed by creating a MATLAB code (fig 2g) to compute three statistical parameters: the standard deviation, the root mean squared (RMS), and the mode. Each mathematical parameter was calculated using three predefined MATLAB functions, which work based on their respective mathematical formulas (figs 2d,2e,2f), and using the EEG signals data points as inputs to perform the calculations.

$$\sigma = \sqrt{\frac{\sum (x - \text{mean})^2}{n}}$$

x is a set of numbers

mean is the average of the set of numbers

n is the size of the set

σ is the standard deviation

Figure 2d: Standard deviation formula

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

where,

predicted$_i$ *= The predicted value for the ith observation.*

actual$_i$ *= The observed(actual) value for the ith observation*

N *= Total number of observations.*

Figure 2e: Root mean square formula

$$M_o = l + \left(\frac{f_1 - f_0}{2f_1 - f_0 - f_2}\right)h$$

Where

l = lower limit of the modal class,

h = size of the class interval (assuming all class sizes to be equal),

f_1 = frequency of the modal class,

f_0 = frequency of the class preceding the modal class,

f_2 = frequency of the class succeeding the modal class.

Figure 2f: Mode formula

.

```
function [statistics] = EEG_analysis (a)
a = table2array(a);
for i = 1:5
a(1,:) = [];
i = i+1;
end
x = mode(a);
y = std(a);
z = rms(a);
input = [x; y; z];
statistics = reshape(input, 9, 1);
end
```

Fig 2g: code used for mathematical analysis.

III- Artificial neural network

Artificial Neural Networks (ANN) are inspired by the human brain, mimicking the way that biological neurons signal to one another [5]. The ANN was used to detect patterns in our data and differentiate facial gestures from each other. An input matrix containing our processed data was entered into the ANN and it returned an output matrix that indicates which gesture was being performed by the user [6].

The input layer receives the data, which is then processed by the hidden layers, and finally, the output layer produces the predictions.

One of the popular tools for building artificial neural networks is MATLAB, a numerical computing environment widely used in engineering and scientific research. Within MATLAB, there is a built-in function called the neural network toolbox (fig 3a), which provides a variety of tools for creating, training, and simulating artificial neural networks.

For this research, we created a feedforward neural network (fig 3b), which consists of an input layer, one or more hidden layers, and an output layer. This type of network is suitable for solving classification and regression problems, which require predicting an output based on an input.

To create a two-layer feedforward neural network using MATLAB's neural network toolbox, one can use the nprtool, a graphical user interface that simplifies the process of designing and training a network. This tool allows users to load data, configure the network architecture, and train the network using various training algorithms.

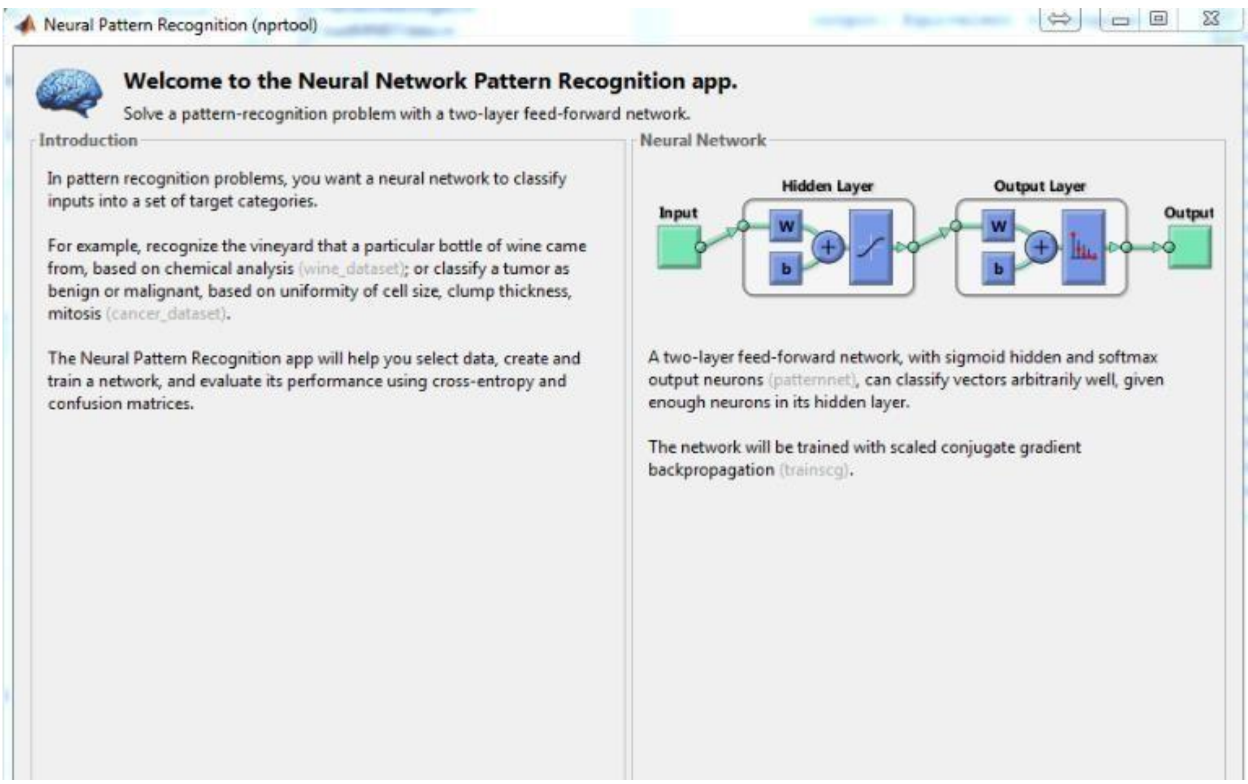


fig 3a: Neural Network Toolbox in MATLBA

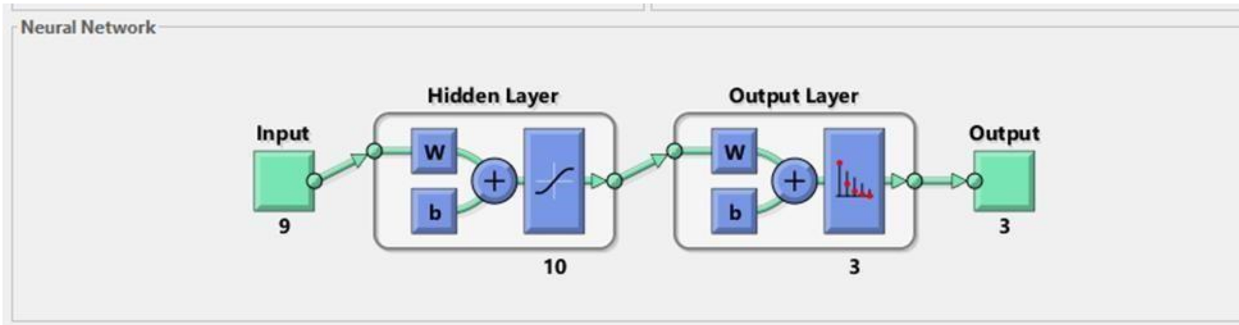


Fig 3b: Feedforward neural network created using MATLAB npr tool

In order to train a neural network using nprtool in MATLAB, one needs to first prepare the data. The data should be divided into three sets: training set, validation set, and testing set. The training set is used to train the network, the validation set is used to tune the network's hyperparameters and prevent overfitting, and the testing set is used to evaluate the network's performance on unseen data.

the data is divided into three sets based on a ratio of 70:15:15 (fig 3c). This means that 70% of the data is used for training, 15% is used for validation, and the remaining 15% is used for testing. This ratio is a common practice in machine learning, as it provides a good balance between training and testing the network.

The network is trained by adjusting the weights between the neurons based on the input and output data. The training process continues until the network's error on the validation set stops improving or starts to worsen. This is done to prevent overfitting, which occurs when the network becomes too specialized to the training data and fails to generalize to new data.

Finally, the trained network is evaluated on the testing set to measure its performance on unseen data. The performance of the network is measured using various metrics, such as accuracy, precision, recall, and F1 score.

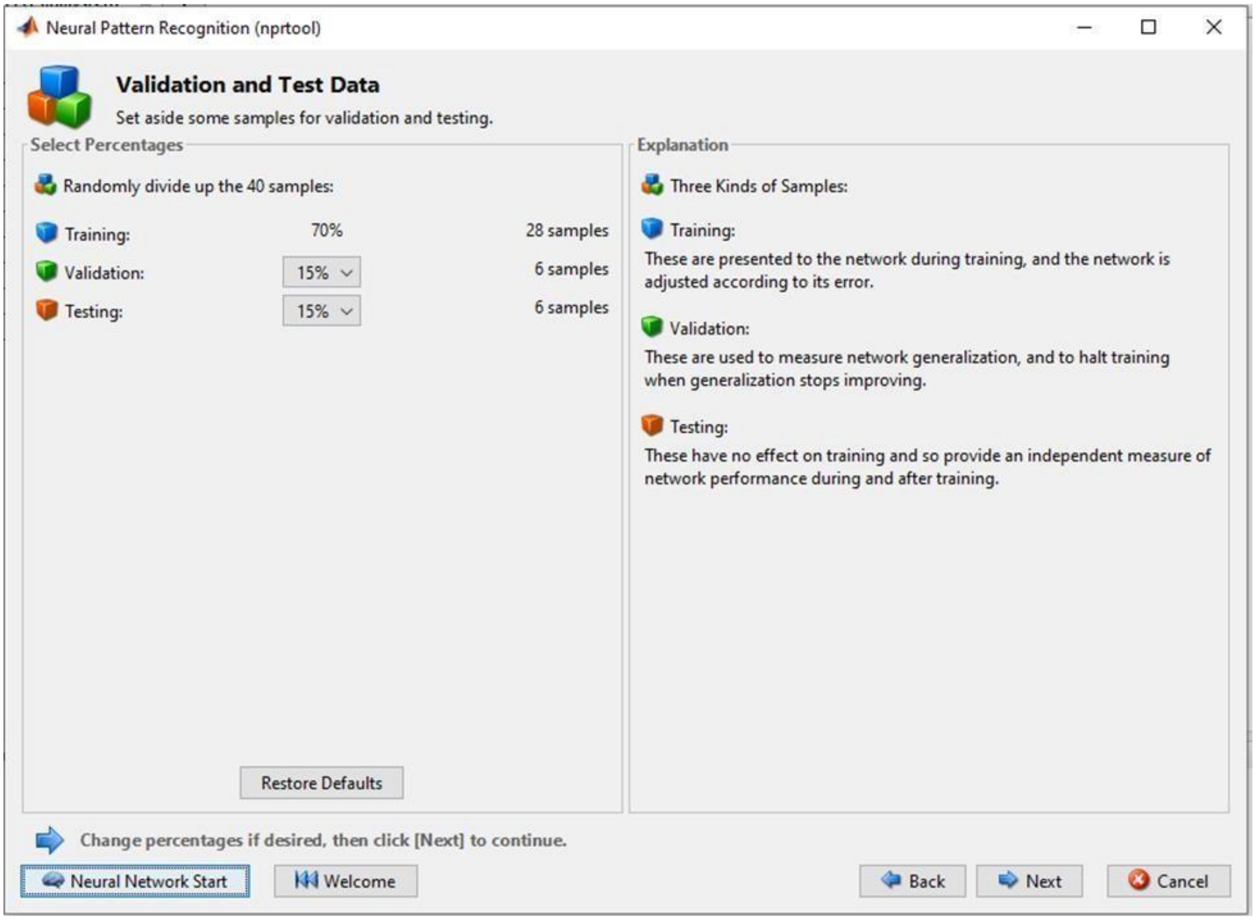


Fig 3c: Validation and test of the neural network

After the neural network has finished training, we can use the confusion matrix to evaluate its performance (fig 3d). The confusion matrix allows us to calculate various performance metrics, such as accuracy, and precision, recall, and F1 score. Accuracy is the ratio of correctly classified instances to the total number of instances in the data set. Precision is the ratio of true positives to the sum of true positives and false positives. Recall is the ratio of true positives to the sum of true positives and false negatives. The F1 score is the harmonic mean of precision and recall.

The confusion matrix provides valuable insights into the performance of the neural network. For example, if the confusion matrix shows a high number of false positives, it indicates that the model is incorrectly predicting positive classes. On the other hand, if the confusion matrix shows a high number of false negatives, it indicates that the model is incorrectly predicting negative classes. By analyzing the confusion matrix, we can identify the strengths and weaknesses of the neural network and make improvements as necessary.

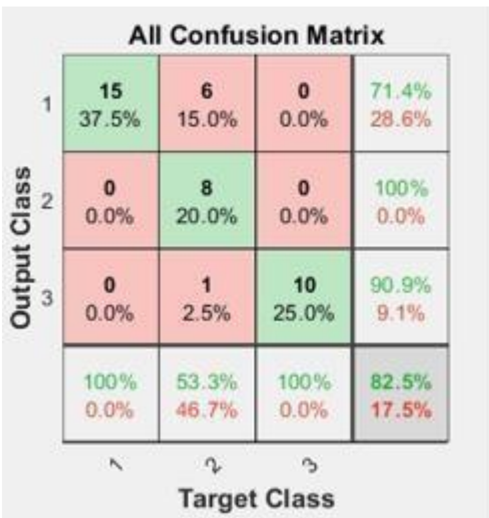


Fig 3d: Confusion metrix of the neural network created

After the neural network was trained, we had the option to convert it into a function using the nprtool in MATLAB. The function (fig 3e) created is capable to tell which of the three movements is performed by the subject based on the EEG signals detected by the flat electrodes.

```
function [Y,Xf,Af] = myNeuralNetworkFunction(X,~,~)
```

Fig 3e: Neural Network function created

IV- Drone control using neural network

After the neural network has been trained, it is used to predict the class of the input gestures, and the output is used to execute specific commands on a drone.

In order to execute these commands, conditional statements are used in MATLAB to process the output from the neural network. Conditional statements, also known as if-else statements, are used in programming to execute different blocks of code based on a specific condition. In this case, the output from the neural network serves as the condition for the conditional statements.

The first conditional statement may be used to execute a specific command if the neural network predicts the gesture to be a "takeoff" gesture. This command could initiate the drone to take off and begin flight. The second conditional statement may be used to execute a specific command if the neural network predicts the gesture to be a "land" gesture. This command could initiate the drone to land safely. The third conditional statement may be used to execute a specific command if the neural network predicts the gesture to be a "move" gesture. This command could initiate the drone to move in a specific direction or to a specific location based on the gesture.

By using conditional statements, the drone can be programmed to respond to specific gestures in a predetermined way. This can provide a level of automation and precision that can be incredibly useful in various applications. For example, this type of technology could be used in search and rescue operations, where the drone could be controlled by hand gestures, allowing rescuers to keep their hands free for other tasks.

RESULTS:

We have collected and processed data from a variety of facial gestures using three different subjects. The gestures used in this project were: raising eyebrows, looking right, and hard blinking. The three gestures were performed by each of the three subjects with each of them performing a minimum of 5 sessions for each gesture. The results of the training, validation, and testing of the ANN is provided in the confusion matrix shown in fig.3d. From the results we can see that the ANN has an accuracy of 82%. After the ANN was designed and tested, it was transformed into a function used to send command signals to the Tello drone. In the experimental part, we were able to successfully control the drone using the 3 facial gestures selected for this project.

DISCUSSION AND CONCLUSION:

In this research endeavor, data pertaining to various facial gestures have been meticulously collected and processed from a pool of three distinct subjects. The gestures under scrutiny in this project include raising eyebrows, looking to the right, and hard blinking. Notably, each of the three subjects executed each gesture no less than five times, enabling a robust data set to be obtained. The obtained data was then utilized to effectively train, validate, and test an artificial neural network (ANN), with the resultant output presented in the form of a confusion matrix. the ANN exhibits an accuracy of 82%, indicating that it can precisely recognize the targeted facial gestures. Subsequently, the ANN was transformed into a functional tool capable of transmitting command signals to the Tello drone. Notably, in the experimental phase, successful manipulation of the drone using the three designated facial gestures was effectively achieved, affirming the reliability and functionality of the ANN. Also, given that the neural network was constructed using data obtained from multiple volunteers, it is highly likely that it can successfully recognize and interpret the designated facial gestures from any individual, provided that they execute the gestures accurately and in accordance with the established guidelines.

FUTURE WORK:

In order to embark on the development of this research, the team opted for the use of MATLAB due to its fundamental approach towards machine learning and neural networks. The software proved to be an excellent choice for the team as it allowed for a comprehensive understanding of the potential outcomes that could be achieved in the facial gesture classification process.

However, while MATLAB provided a solid foundation for the research, it was recognized that the addition of more libraries and better overall interaction with the drone would necessitate the use of a more robust programming language, such as Python. Python's expansive collection of libraries and its ability to seamlessly integrate with the drone made it an optimal choice for the team to expand the current gesture and drone commands.

It is important to note that for these types of systems to become more practical, a larger repertoire of gestures and drone control movements must be added. As such, the team recognizes the need to incorporate more diverse movements and gestures to ensure the system is capable of adapting to a broader range of commands and user interactions. This will inevitably require a more complex and intricate system, which the team is prepared to tackle head-on in order to achieve their research goals.

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