A Drone Flight Control Using Brain Computer Interface and Artificial Intelligence

Mokhles M. Abdulghani
Jackson State University
Jackson, Mississippi
mokhles.m.abdulghani@students.jsums.edu

Arthur A. Harden
Jackson State University
Jackson, Mississippi
arthur.a.harden@students.jsums.edu

Khalid H. Abed
Jackson State University
Jackson, Mississippi
khalid.h.abed@jsums.edu

***Abstract*— The human mind is a truly remarkable thing that does so much that we are not even aware of. Controlling machines using the concept of Brain-Computer Interface (BCI) is a practical method that opens the way to a fully synchronized method between human thoughts and controlled objects. Using BCI to control a drone will open the way toward smooth and high-response flight. Deep learning is a new-age skill that has made many breakthroughs and influenced modern technologies. It has made it possible to predict and identify even the most complex and abstract patterns that even we humans would be very challenged to catch ourselves. In this paper, a method of controlling a drone using BCI has been presented using an 8-channel Electroencephalogram (EEG) headset. Deep learning has been employed to process and classify human brain waves. After testing the resulting deep learning algorithm, the overall classification accuracy was 90% to distinguish between four different movements of the drone.**

Keywords: *Deep Learning, DL, EEG, Brain-Computer Interface, BCI, Brain-Machine Interface, ECOG, SSVEP, RNN, BMI, LSTM.*

I. INTRODUCTION

Throughout the human lifespan, we have always been extremely fascinated by the human brain. This organism is responsible for two hundred thousand years of progress, creativity, reasoning, and so much more. The human brain's capability to learn, understand, and identify has never been fully recreated due to how much information we can store, identify, relate, and process later. The human brain has been studied to a point of understanding that we have made machines that can closely replicate functionalities, such as the core concept of thinking called Neuron Mapping. Modern times have made it possible to record information about our brains and investigate their functionality. With this capability, we can now ask what possibilities we can do now with this knowledge and technology. Technology and the deep learning concept have advanced to the point where we have also created devices that can interpret our thoughts and make decisions like humans [1] and [2].

There are a few methods that we can apply to make a prosthetic to return someone's limb, and control machines with a thought or movement, such as for people who need wheelchair assistance [3], [4], [5]. We can even give a speech to a person who is mute. Now, how will we do this? Through electroencephalogram (EEG) waves. An EEG is a test that measures electrical activity in the brain using small electrodes usually attached to the scalp. With this type of thinking, we can bring so much joy and comfort to anyone's life. This can enable us all to feel complete and restore senses we have lost or never had for some people. Understanding the extent of this problem has caused us to research far beyond just engineering but to dive into biomedical and psychology to understand the extent of how brain neurons work as well as understanding what can cause a person's specific neurons to fire and then manipulate the signal.

II. RELATED WORK

Deep learning is a fascinating tool that is used but is not limited to analyzing, processing and classifying EEG data. The main obstacle in obtaining an acceptable EEG dataset is the type of sensors or the EEG headsets used in the data acquisition stage, which usually are quite expensive and difficult to use [11]. Ramsey [7] has achieved 85% accuracy in an Electrocorticogram (ECOG) prediction by decoding selected performed tasks and extracting the pattern feature. The methods in [12] have achieved accuracies of only 74.8 % on average for the EEG dataset feature Steady-State Visual Evoked Potential (SSVEP) extraction. While [13] took the power of deep learning networks and employed the Recurrent Neural Network (RNN) to classify the EEG dataset and extract the features over time. The achieved accuracy was 81%. Long Short-Term Memory (LSTM) networks have been used in [14] and [15]. In [14] 68.7% accuracy of brainwave classification has been achieved. EEG dataset has been obtained while providing a formula (True Positive + True Negative / True Positive + False Positive + False Negative + True Negative). A low-cost EEG solution has been used in [16]; therefore, an accuracy of 40% has been achieved in classifying EEG in this method

979-8-3503-2028-2/22/$31.00 ©2022 IEEE
DOI 10.1109/CSCI58124.2022.00148

of datasets. There have been many more instances of using BCI to control devices [2], [6], and [16], but not many can fly like a drone. In [17], researchers suggested using software such as the V-rep, which can be used to simulate any machine (such as a drone) in a virtual reality rather than testing on a real system.

In this research, a low-cost 8-channel EEG headset has been used to process and classify human brain waves while looking at a drone and imagining the commands; on the other hand, we used a 14-channel EEG headset in our previous study [18]. LSTM-RNN has been selected to classify the brainwaves and extract temporal features from the time-series input signals with different frequencies and lengths. LSTM-RNN has improved the accuracy of EEG brainwave data classification. Moreover, the overfitting problem in the learning process has been avoided by analyzing and possessing the EEG dataset prior to getting them to the learning stage. The rest of this paper is organized as follows. The methodology used, recording the EEG data, processing the EEG data, training the deep learning algorithm, results and analysis, and conclusion and future works.

III. METHODOLOGY

The Unicorn hybrid black + EEG headset is manufactured by *G.tec* and has an 8-channel recording portion to record the brain activities. This method was chosen to record the electrical activity in the brain, which is normally measured from the scalp. The drone, shown in Figure 1, is a small quadcopter that is connected via Universal Data Protocol (UDP) [9]. Python has been used for compatibility with drone communication. The idea proposed is to record the activity of specific drone commands. Four commands have been used to control the drone as follows: Forward, Backward, Rotate, and Stop. Once the commands are recorded, a deep learning algorithm has been used to identify each command. The deep learning algorithm is an LSTM. Figure 2 shows the *G.tec Unicorn hybrid black +,* 8-channel EEG headset [5], and Figure 3 shows the brain interface nodes [10].

Figure 1: Tello drone [9].

Figure 2: G.tec Unicorn hybrid black + EEG headset [5].

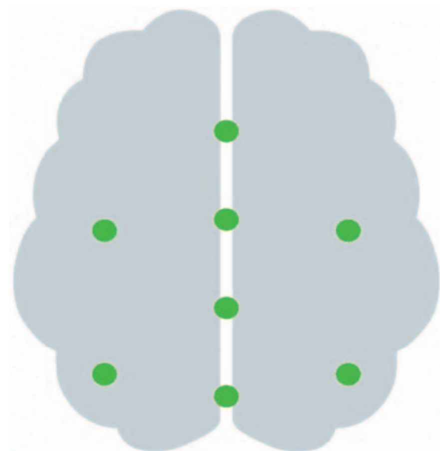

Figure 3: Brain interface nodes [10].

The brain waves classification has been done using deep learning as follows:

- **Recording the EEG data:** In the recording, there was a total of seventeen channels including the Accelerometer, Gyro, Counter, Battery, and Valid. When we first did our initial recording, we went for a seesaw motion for forward and backward thinking. We could eliminate the need to split eight channels into four and become more accessible. After the next session of recording, there was a way to confirm which nodes were on. Eight-channel signals have been recorded using *G.tec Unicorn hybrid black* headset during 25 sessions of thinking of commands, which are: Forward, Backward, Rotate and Stop (25 sessions for each command). In the 25 sessions, the EEG data has been recorded from a 21-year-old male participant, and each session took from 2 to 10 seconds. Although the resulting data has a different time frame, our suitable deep learning algorithm will deal with this issue later. Figure 4 shows a sample of the recorded row EEG signals using the 8-channel *G.tec Unicorn hybrid black* headset.

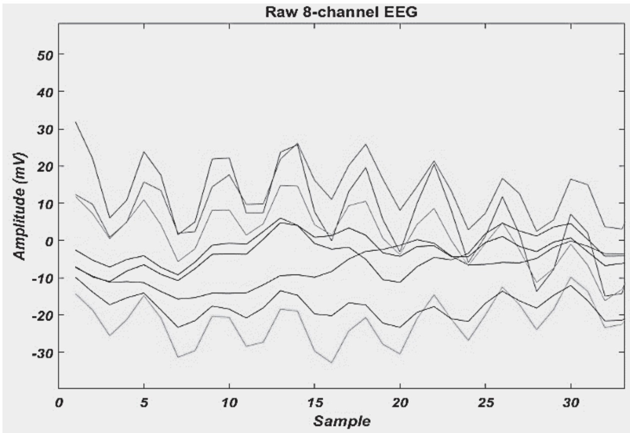

Figure 4: A Sample of raw EEG signal set.

- **Processing the EEG data:** Before we could train the LSTM algorithm, we had to take raw EEG signals data and normalize it. This was done to enhance the accuracy of the output classification. The data has been divided into testing and training data, so we considered 20% for testing and 80% for training. Each of the 8-recorded EEG channels consists of different frequencies with different amplitude ranges. This is what made it necessary to normalize the EEG data for our algorithm. This also helps speed up the training process and obtain as many accurate results as possible. The training and testing data have been normalized by calculating the pre-feature mean and standard deviation for all of the input sequences. Then, the mean value will be subtracted from each of the testing and testing observations and the results for both of them have been divided by the standard deviation as follows:

$$EEG_{\ Norm} = \frac{x - \mu}{\sigma}$$

(x) is the recorded raw EEG signal, (μ) is the mean value, and (σ) is the standard deviation for the recorded row EEG signals. After the normalization process has been done for all the recorded sessions, the EEG data was then ready for the training process.

- **Training LSTM network:** The processed EEG signals have been used then to train a deep learning model using the LSTM model on MATLAB 2023a. LSTM is mainly constructed to deal with sequence-input signals, which is the case we deal with (8-time series EEG signals) and one vector output (1024,2048,4096,8192). The LSTM model has been designed as sequence-input to vector-output with the following layers: sequence-input layer has a number of features equivalent to the number of channels (8 channels) of the recorded EEG signals (8 channels), three LSTM layers with 160 hidden units for each separated by a drop-out layer to deal with the overfitting during the learning process. The dropout layers will randomly shut off 20%, 20%, and 20% of the training parameters in the 1st, 2nd, and 3rd LSTM layers, respectively (dropout ratios 0.2, 0.2, and 0.2). Finally, the network has ended with Fully Connected, SoftMax, and classification output layers with the four class labels (equivalent to the required number of outputs) as illustrated in Figure 5. The 90% accuracy that has been achieved in the training process for the four commands (Forward, Backward, Rotate and Stop) is shown in Figure 6.

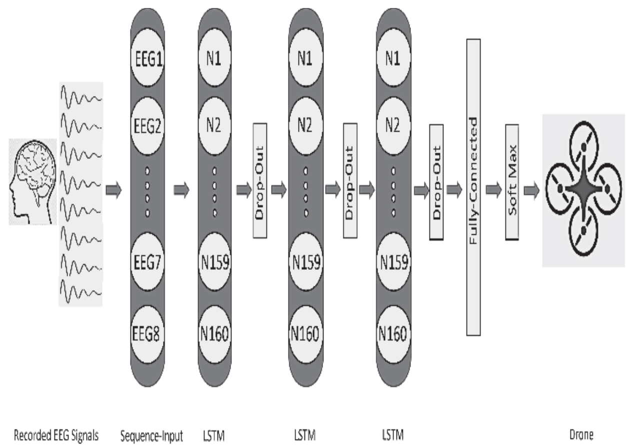

Figure 5: The structure of the RNN-LSTM model

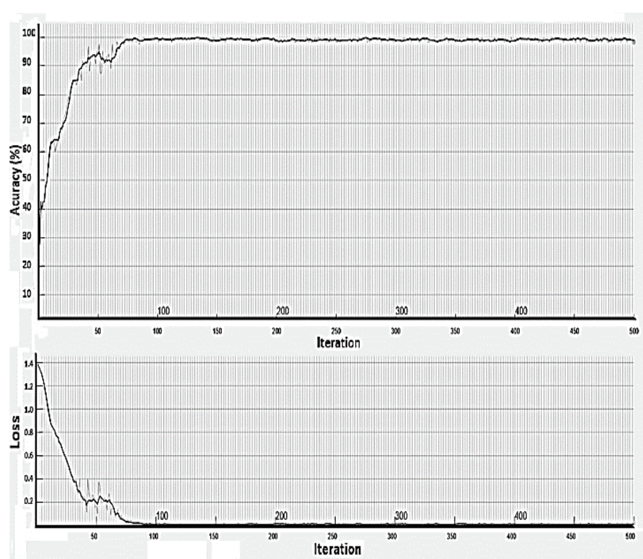

Figure 6: LSTM accuracy after the training process

V. RESULTS AND ANALYSIS

The 90% accuracy has been achieved when testing the resulting LSTM network with the remaining 20% of the normalized EEG dataset. These results have been obtained with the help of the adaptive moment estimation (Adam) algorithm. The Adam algorithm has been used as an optimization algorithm to tune the hyper-parameters of the LTSM-RNN model. After training the LSTM-RNN model on 80% of the recorded EEG dataset with 500 max epochs and a mini-batch size of 20, the 90% accuracy has been archived. Figure 6 shows the accuracy in the training stage. Table 1. Shows the predicted outputs for the designed LSTM-RNN model to classify the EEG dataset.

Table 1. The predicted outputs of the LSTM-RNN network.

Input (8-channel EEG signal)	Desired Output	Predicted Output
Forward	1024	1024
Forward	1024	1024
Forward	1024	1024
Forward	1024	1024
Forward	1024	2048
Backward	2048	2048
Backward	2048	2048
Backward	2048	2048
Backward	2048	2048
Backward	2048	2048
Rotate	4096	4096
Rotate	4096	4096
Rotate	4096	2048
Rotate	4096	4096
Rotate	4096	4096
Stop	8192	8192
Stop	8192	8192
Stop	8192	8192
Stop	8192	8192
Stop	8192	8192

V. CONCLUSION AND FUTURE WORK

This research showed a promising method for controlling a drone flight and navigation path using human brain signals or brain-computer interface and artificial intelligence. Employing the concept of deep learning in this research has shown acceptable to good accuracy (90%) in distinguishing between four commands (Forward, Backward, Rotate and Stop) represented by one's thoughts or by a BCI system. The *8-channel G.tec Unicorn Hybrid Black+* was a great choice compared with the more expensive *16-channel EMOTIV Epoc+*, where it was possible to record the data and monitor them on MATLAB.

Further work will be considered to have more than one participant and more than four commands, and the desired goal will be %100 accuracies in the LSTM algorithm. Moreover, a real-time test will be performed to come out with a real system where the *G.tec* EEG headset also offers the ability to design a BCI system using Simulink on MATLAB.

REFERENCES

[1] K. M. Al-Aubidy and M. M. Abdulghani, "Wheelchair Neuro Fuzzy Control Using Brain Computer Interface", *12th International Conference on Developments in eSystems Engineering (DeSE)*, pp. 640-645, 2019.

[2] H. Raad, F. Fargo, O. Franza, "Autonomic Architectural Framework for Internet of Brain Controlled Things (IoBCT)". ISNCC 2021.

[3] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H.Falk, and J. Faubert, "Deep learning-basedelectroencephalography analysis: a systematic review," J. Neural Eng., vol. 16, no. 5, p. 051001, Aug. 2019.

[4] J. J. Bird, D. R. Faria, L. J. Manso, A. Ekárt, and C. D.Buckingham, "A Deep Evolutionary Approach toBioinspired Classifier Optimisation for BrainMachineInteraction," Complexity, vol. 2019, pp. 1–14, Mar. 2019.

[5] W. Chen et al., "EEG-based Motion Intention Recognition via Multi-task RNNs," in Proceedings of the 2018 SIAM International Conference on Data Mining, Philadelphia, PA: Society for Industrial and Applied Mathematics, 2018, pp. 279–287.

[6] M. Iijima and N. Nishitani, "Cortical dynamics during simple calculation processes: a magnetoencephalography study," Clinical Neurophysiology Practice, vol. 2, pp. 54–61, 2017.

[7] Nicolas F Ramsey. "Exploration of the brain for optimal placement of BCI implants in paralyzed people" IEEE section II, 2014.

[8] Donatella Mattia, Laura Astolfi, Jlenia Toppi,Manuela,P tti,Floriana, Pichiorri, Febo Cincotti "Interfacing brain and computer in neurorehabilitation" section II, 2016.

[9] J. J. Bird, D. R. Faria, L. J. Manso, A. Ekárt, and C. D. Buckingham, "A Deep Evolutionary Approach to Bioinspired Classifier Optimisation for Brain Machine Interaction," Complexity, vol. 2019, pp. 1–14, Mar. 2019.

[10] W. Chen et al., “EEG-based Motion Intention Recognition via Multi-task RNNs,” in Proceedings of the 2018 SIAM International Conference on Data Mining, Philadelphia, PA: Society for Industrial and Applied Mathematics, 2018, pp. 279–287.

[11] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H. Falk, and J. Faubert, “Deep learning-based electroencephalography analysis: a systematic review,” J. Neural Eng., vol. 16, no. 5, p. 051001, Aug. 2019.

[12] Lim, Jeong-Hwan, Han-Jeong Hwang, and Chang-Hwan Im. "“Eyes-closed” SSVEP-based BCI for binary communication of individuals with impaired oculomotor function." 2013 International Winter Workshop on Brain-Computer Interface (BCI). IEEE, 2013.

[13] Bozhkov, Lachezar, and Petia Georgieva. "Overview of deep learning architectures for EEG-based brain imaging." 2018 International Joint Conference on Neural Networks (IJCNN). IEEE, 2018.

[14] Kumar, Sushil, et al. "Bug Report Classification into Orthogonal Defect Classification Defect Type using Long Short Term Memory." 2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N). IEEE, 2021.

[15] Siagian, Pandapotan, and Erick Fernando. "Long Short Term Memory Networks for Stroke Activity Recognition base on Smartphone." 2021 IEEE 5th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE). IEEE, 2021.

[16] Farmaki, Cristina, et al. "Application of dry EEG electrodes on low-cost SSVEP-based BCI for robot navigation." 2022 IEEE International Conference on Imaging Systems and Techniques (IST). IEEE, 2022.

[17] Abdulghani, M. M. Al-Aubidy, K.M. “Design and evaluation of a MIMO ANFIS using MATLAB and V-REP” 11th International Conference on Advances in Computing, Control, and Telecommunication Technologies, ACT 2020; Virtual, Online; 28 August 2020 through 29 August 2020, ISBN: 978-171381851-9.

[18] M. M. Abdulghani, O. Franza, F. Fargo and H. Raad, "Brain Waves Pattern Recognition Using LSTM-RNN for Internet of Brain-Controlled Things (IoBCT) Applications," *2022 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)*, 2022, pp. 1-5, doi: 10.1109/ IEMTRONICS55184.2022.9795715.