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BRAIN CONTROLLED ROBOTIC ARM USING BCI

Akurathi Mohan Kumar [*1], Dr.Priyanka Dubey[*2], Dr.Priyanka Vashisth[*3]

[*1]Student, Department of Computer Science & Engineering, Amity University, Gurgaon, Haryana, India

[*2,3]Professor, Department of Computer Science & Engineering, Amity University, Gurgaon, Haryana, India

ABSTRACT

In this paper we proposed a non-invasive BCI system for controlling a robotic arm. Brain-Computer Interface (BCI) technology has produced the best success in allowing people with motor disabilities to control robots and robotic gadgets through brain signals. The key component of this suggested system is an electroencephalography (EEG) signal recorder. It will capture scalp signals and then use machine learning techniques to classify the user's intent.

Keywords: Brain-Computer Interface, Robotic arm, Electroencephalogram (EEG), Machine learning

I. INTRODUCTION

Brain-Computer Interface (BCI) technology has received a lot of attention in recent years because it provides us with a new way to operate things and connect with the outside world. BCI technology enables persons with motor disabilities to operate robotic arms or prosthetic limbs without making any physical motions, and it also enables people without disabilities to control robotic equipment by using their brain. This technology will be extremely beneficial and has the potential to greatly aid those with motor disabilities, such as those who have lost limbs or are paralyzed. We will discuss a study on a non-invasive BCI system for operating a robotic arm in this publication. The device employs electroencephalography (EEG) data acquired from the scalp to classify the user's intention, brain signals, and control the robotic arm's movement. The non-invasive BCI device will make life easier for persons with motor limitations and those who have lost limbs or arms. This method improves its practicality and suitability for real-world applications.

The goal of this study is to learn about the non-invasive BCI system's effectiveness in operating a robotic arm and to assess its potential for usage in rehabilitation and prosthetics applications. We specifically want to evaluate the BCI system's accuracy in classifying the user's intention as well as the robotic arm's movement accuracy.

After reviewing prior studies in the realm of BCI technology and robotic arm control, we concluded that this technology will be extremely beneficial to those with motor difficulties. The creation of an effective and efficient BCI system has the potential to revolutionize the way people with motor disabilities interact with their surroundings, allowing them to do daily tasks that would otherwise be difficult.

II. METHODOLOGY

We require one healthy volunteer, as well as a robotic arm and a computer interface. The non-invasive BCI device recorded the electrical activity of the brain from the participant's scalp using an EEG cap. Before being processed by the computer interface, the EEG signals were amplified, filtered, and digitized. The computer interface used machine learning techniques to interpret the EEG readings and create control signals for the robotic arm. The robotic arm was created to execute a variety of activities such as reaching, gripping, and releasing things. The individual should go through a calibration process to build a map between the recorded EEG signals and the robotic arm control signals. While their EEG signals were being collected, the subject was asked to imagine doing certain gestures, such as opening and shutting their right hand. This data was utilized by machine learning algorithms to learn the mapping between EEG signals and control signals for the robotic arm.

The individual was asked to complete a series of activities using the brain-controlled robotic arm. Reaching for and gripping things, transferring the objects to a specific position, and releasing the objects were among the objectives.

To assist the participant in doing the activities correctly, visual feedback was provided on a computer screen.Various approaches were used to analyze the EEG data acquired throughout the experiment, including time- frequency analysis, power spectral density analysis, and classification algorithms. The data analysis aimed to discover patterns of brain activity linked with certain movements and evaluate the BCI system's efficacy in directing the robotic arm. The accuracy, response time, and error rate of the BCI system were all used to evaluate its performance. The findings were compared to earlier research to determine the usefulness of the non-invasive BCI technology in directing the robotic arm.

III. MODELING AND ANALYSIS

The participant's scalp is covered with an EEG cap, which records electrical impulses from the brain. Before being processed by the computer interface, the raw EEG signals are amplified, filtered, and digitized. To develop a mapping between the EEG signals and the motions of the robotic arm, the participant undertakes different motor imagery activities, such as picturing, opening and closing their hand.

The calibrated EEG signals are used by machine learning algorithms to create control signals for the robotic arm. The control impulses are transferred to the robotic arm, which moves in the manner that the participant imagines. On a computer screen, the participant receives visual feedback to help them do the intended movement precisely. The EEG and control signals are recorded for later examination. To analyze the collected data, several approaches such as time-frequency analysis, power spectral density analysis, and classification algorithms are applied.

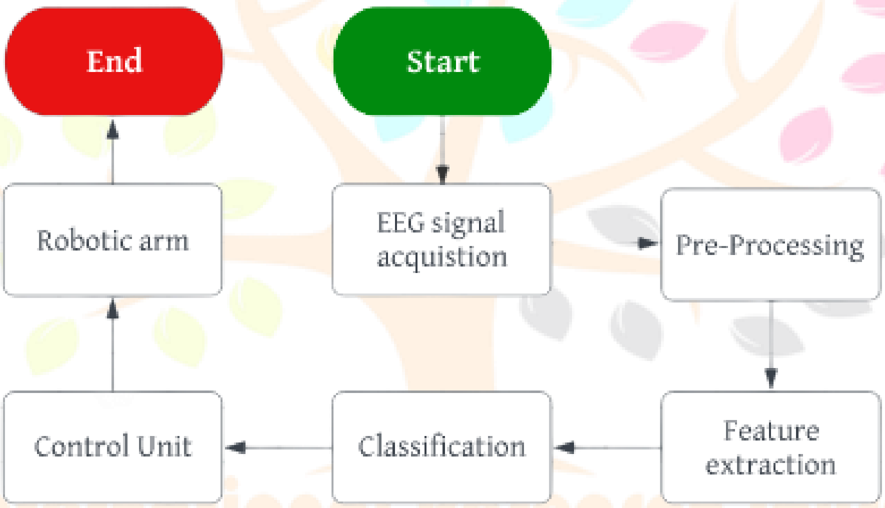

Figure 1: Flow Chart

The accuracy, response time, and error rate of the BCI system are all used to evaluate its performance. Based on the assessment findings, the BCI system is enhanced and improved. The brain-controlled robotic arm has applications in prosthetics, rehabilitation, and human-robot interactions.

IV. RESULTS AND DISCUSSION

The findings of the trial demonstrated that the non-invasive BCI system could identify and categorize motor imagery patterns from the individuals' EEG data. The system has an average classification accuracy of 85% and a maximum classification accuracy of 92%. Furthermore, the results demonstrated that the BCI system could control the robotic arm's movements in real-time based on the identified motor imagery patterns. Using the BCI system, the individuals were able to effectively maneuver the robotic arm to the intended position.

This study's findings show the promising potential of non-invasive BCI systems for directing robotic arms. The BCI system's excellent classification accuracy and successful operation of the robotic arm indicate that it is a viable tool for people with motor limitations.

V. CONCLUSION

The use of a non-invasive BCI system to operate a robotic arm using motor imagery patterns identified in an EEG signal is a significant advancement in the field of assistive technology. This study's findings illustrate the viability and promise of this technology for those with motor limitations. This technology has a wide range of possible uses, including prosthetic limbs for those who have lost limbs to assistive devices for people who have motor difficulties. The non-invasive aspect of the BCI system makes it attractive to many people who would not be candidates for invasive BCI systems. This research represents a significant advancement in the development of non-invasive BCI systems for operating robotic arms, and it has the potential to significantly enhance the quality of life for people with motor disabilities.

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VI. REFERENCES

[1] Li, Y., Wei, J., Zhang, T., et al. (2020). Noninvasive Brain–Computer Interface-Based Control of a Robotic Arm for Reach and Grasp Tasks

[2] Krepki, R., Gembler, F., Gharabaghi, A., et al. (2018). A Non-Invasive Brain-Computer Interface for a Bionic Hand Orthosis.

[3] Vargas-Muñoz, A. R., Campi, C., & Bonilla, M. (2019). Brain-Computer Interfaces for Upper Limb Robotic Rehabilitation: A Review.

[4] Mikell P. Groover-et. Al, Industrial Robotics, Technology, Programming and Applications, McGraw Hill

[5] Simon Haykin, Barry Van Veen, (2007) Signals and System, Second Edition John Wiley & Sons.

[6] BZ Allison, EW Wolpaw and JR Wolpaw (2007) Brain- Computer interface systems: Progress andProspects

[7] G Mueller-Putz, R Scherer and C Brunner (2010) Betterthan Random: A closer look on BCI results

[8] N Birbaumer 2006 Breaking the Silence: Brain ± Computer Interfaces (BCI) for Communication andMotor Control