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Neural Command: Real-Time EEG-Based Brain-Computer Interface for Assistive Robotic Control

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***Abstract*—This paper presents a method to help people with disabilities interact with their surroundings using brainwave signals. Since individuals with disabilities often depend on different types of transportation, this research focuses on enabling the real-time control of a robotic vehicle through non-invasive brain-computer interfaces (BCI).Can brain-computer interfaces (BCIs) based on EEG signals control a robotic car in real time? The MUSE headband is used to capture brain waves, and the signals are processed through PETAL metrics and a server within a Brain Wave Processing Unit. Subsequently, they are transmitted via WiFi/IPv4 to a Vehicle Control Unit with esp8266 microcontroller. The system underwent rigorous evaluation, achieving an 85% control accuracy and an average response time of 300 milliseconds. These results highlight the system's effectiveness in real-time applications, offering precise and rapid response capabilities suitable for assistive technology. This research represents a contribution to the development of advanced BCI-based assistive devices, demonstrating the potential for improved human-machine interaction. The high accuracy and low latency of the system emphasize its suitability for environments where swift and reliable control is crucial, particularly for individuals with mobility impairments.**

***Index Terms*—BCI, Robotic car, TCP,EEG signal,non-invasive.**

I. Introduction

Disabilities affect a significant portion of the global population, impacting individuals' ability to engage with their surroundings and perform daily tasks. According to a 2022 WHO and UNICEF report, over 2.5 billion people require assistive products like wheelchairs and communication tools, highlighting the urgent need for effective assistive technologies, especially for those with severe mobility impairments [1] [2]. In Bangladesh, 18.47% of individuals with disabilities rely on assistive devices, but for those unable to move their hands, traditional devices are inadequate. For these individuals, alternative methods like eye blinks are crucial for independence [3].

To address this challenge, this study proposes a novel method for controlling a robotic vehicle using brainwave signals, specifically designed for individuals with severe mobility impairments. The system translates eye blinks into actionable commands through the use of non-invasive brain-computer interfaces (BCIs) based on EEG signals. This approach offers a practical and user-friendly solution for enhancing mobility and autonomy for those who are most in need.

The research is organized into three key components: the Brainwave Acquisition Unit, Robotic Vehicle, and Signal Processing and Control Logic. The MUSE headband captures brainwave signals, which are processed in Python to control the ESP8266-powered robotic vehicle wirelessly. EEG data is sampled at 256 Hz, with blink detection handled by a peak detection algorithm.

This study aims to use EEG technology to bridge the accessibility gap for individuals with significant mobility limitations, demonstrating the solution's technical viability and practical benefits to advance more inclusive and efficient assistive technologies.

The document is structured as follows: Section II reviews previous research, Section III details the study's methodology, Section IV presents and analyzes the results, and Section V discusses the findings and suggests directions for future research .

II. RELATED WORKS

Brain-computer interfaces (BCIs) enable real-time control of external devices using brain activity. Studies have explored BCIs for tasks like controlling unmanned ground vehicles (UGVs) using EEG signals, bypassing traditional controls and focusing on key processes like feature extraction and classification [1]–[3]. BCIs have also been effective in multitasking, such as controlling robotic arms, highlighting their potential for human augmentation [4]. Integrating techniques like near-infrared imaging has advanced real-time BCI applications [5]. BCIs improve motor skills, aid in IoT device interaction, and translate brain activity into real-time commands, with CNNs enhancing multi-task prediction [6]–[9].

III. BRAIN EEG AND ELECTRODE

EEG (Electroencephalography) is a non-invasive method for measuring brain electrical activity, commonly used in neurosurgery for diagnosing and monitoring brain function [10]. The electrode, a key component for recording neural activity, has properties influenced by its composition and microstructure, which in turn impact its electrical performance [11].

A. Data Gathering with MUSE

MUSE employs integral-field spectroscopy in the visible range, enhanced by adaptive optics, to achieve high-quality spectral measurements [12]. The frontal lobe, especially the prefrontal cortex, is crucial for decision-making, problem-solving, and motor control, providing essential signals for BCI applications to control external devices like cars [13]–[15].

B. Why Frontal EEG Data?

The frontal lobe (prefrontal cortex), is vital for decision-making, problem-solving, and motor control, all essential for driving, as it involves continuous planning and movement execution [13], [15], [16].

C. Cognitive and Motor Functions

Frontal EEG data, rich in motor planning and cognitive signals, can effectively predict movements and intentions [17], making it ideal for BCI-based vehicle control.

IV. SYSTEM ARCHITECTURE

The system architecture consists of three main components: the Brainwave Acquisition Unit, which captures brainwave signals using MUSE from the human brain; the Brain Processing unit, receives and process the brain signals and generates command to to direct the vehicle's movements. The Vehicle Control Unit, receives the commands wirelessly via ESP8266 and performs movement using motor driver and gear motors. Fig. 1 illustrates the system architecture of Robot vehicle using brain computer interface. A detail description of the components will be given below.

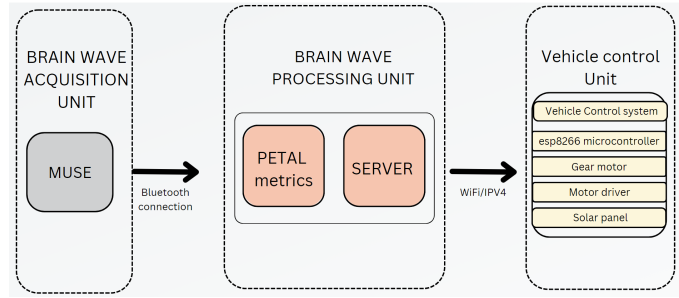

Fig. 1. System Architecture

A. Brain Wave Acquisition Unit

The Muse 2 is a real-time EEG sensor device used in our experiment, featuring four electrodes (TP9, AF7, AF8, TP10). AF7 and AF8 utilize gold sensors, while TP9 and TP10 use rubber sensors, all sampling at 256 Hz with 12-bit depth. These channels measure brain activity ranging from 0.0 to 1682.82 µV. The device also includes an accelerometer and gyroscope and communicates wirelessly via Bluetooth using specialized software.

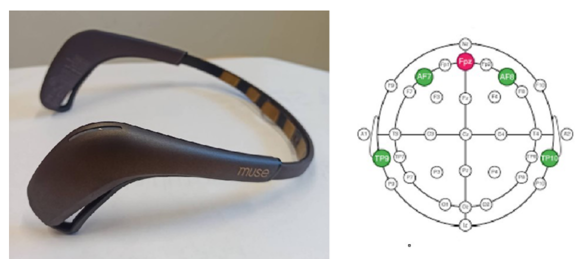

Fig. 2. Head Band with corresponding electrode

Our Muse2 headband with the corresponding electrodes is shown in Fig.2.

B. Brain Wave Processing Unit

This unit consists of two components: 1) Petal Matrices and 2) Server. There description is given below.

1) Petal Matrices: Petal Metrics software collects data from the Muse device via Bluetooth and streams .The PetalStream _eeg channel specifically handles raw data collection, including timestamps, which is then processed by the server

2) Server: The server processes and stores data, focusing on the TP9 channel of the Muse 2. It manages all data processing and robotic vehicle control, detecting upward peaks above 140 µV after normalization.

- **Filtering**
  Several digital filters are applied to enhance the signal and focus on relevant frequency bands. These include:
  - A high-pass filter (0.5 Hz cutoff) to remove baseline drift and slow trends.
  - Band-stop filters to eliminate power line interference (57-67 Hz, 123-127 Hz).
  - A band-pass filter (1-25 Hz) to isolate frequency components relevant to blinks.

Normalization: The EEG data is normalized to a zero mean to establish a baseline for detecting negative peaks and eye blinks, ensuring clear differentiation between positive and negative peaks and preventing missed downward peaks.

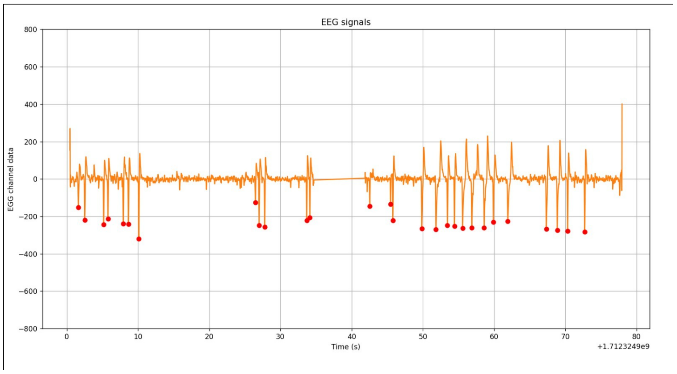

Fig. 3. After filtering Focusing on Delta AF7 and Delta AF8 channels of eye blink

Blink Detection: The system identifies blinks using a peak detection Algorithm 1 adapted for EEG signals. The algorithm operates as follows:

Peak Detection: Peaks are detected in the EEG signal where the amplitude exceeds a threshold (140 µV) as shown at Line 31 of Algorithm 1. A refractory period of 0.15 seconds prevents consecutive detection, ensuring each blink is counted only once.

Blink Counting and Activation: Upon detecting a blink, a timer starts for a 4-second window. During this window, additional blinks are counted. After the 4-second window:

- If no blinks occurred, a 'stop' command (character 'O') is sent to the ESP32.
- If one blink is detected, a 'forward' command is triggered by sending character 'S' to vehicle control unit.
- If two blinks are detected, a 'left' command is triggered by sending character 'L' to vehicle control unit.
- If three or more blinks are detected, a 'right' command is triggered by sending character 'R' to vehicle control unit.

C. Vehicle Unit

Different components of vehicle unit are described below.

- Wireless Controller: The ESP8266 is a cost-effective Wi-Fi microcontroller with a 32-bit processor at 160 MHz, 50 KB RAM, and 2.4 GHz Wi-Fi support. It includes multiple interfaces (UART, SPI, I2C, etc.) and power-saving modes, making it ideal for IoT applications due to its balance of performance and efficiency .
- Motor Driver:
  The L298N dual H-bridge driver controls motor direction and speed, operating at 5V logic and 5V-35V drive voltage, handling up to 2A per bridge with a 25W power limit. It accepts control signals from 4.5V to 5.5V and operates in temperatures from -25°C to +130°C.

Algorithm 1 Blink Detection Implementation Pseudocode

```
1:  Initialize LSL stream
2:  Connect to MUSE headband
3:  Pull EEG samples and store in buffer
4:  while True do
5:      Fetch EEG sample and timestamp from LSL stream
6:      Append EEG sample to window
7:      if sizeOfWindow ≥ buffer_size then
8:          if CountB = 1 then
9:              StartT = CurrentTime
10:             Active = True
11:             CountB = 0
12:         end if
13:         if Active and (CurrentTime - StartT > 4 seconds) then
14:             if AcCount = 0 then
15:                 Send 'O' command to ESP32
16:             else if AcCount = 1 then
17:                 Send 'S' command to ESP32
18:             else if AcCount = 2 then
19:                 Send 'L' command to ESP32
20:             else
21:                 Send 'R' command to ESP32
22:             end if
23:             AcCount = 0
24:             Active = False
25:         end if
26:         Normalize data to have zero mean
27:         Apply high-pass filter to data
28:         Apply band-stop filters to remove interference
29:         Apply band-pass filter to isolate blink-related frequencies
30:         if (secondPastData < immediatePastData > presentData) then
31:             if ((immediatePastData > threshold)) then
32:                 Count blink
33:                 Set LastBlinkTime = CurrentTime
34:             end if
35:         end if
36:         Update buffer: keep last two values for continuity
37:     end if
38:     (e.g., 0 blinks = STOP, 1 blink = FORWARD, etc.)
39:     Determine command based on blink count
40:     Send command to robotic car via Wi-Fi
41: end while
```

- Gear Motors: We used four 6V TT DC gear motors with dual shafts, operating at 3-12V, drawing 40-180mA idle, with a speed of 100-150 RPM and a torque of 0.35 kg/cm. All motors ran at a constant speed without PWM control .
- Solar: The waterproof solar power board has a maximum power of 0.75 W, operating at 150 mA and 5V. It has an open circuit voltage of 6.12V and a short-circuit current of 150 mA, with dimensions of 99 x 69 mm .
- Wireless Network Device: Facilitates communication between the brainwave sensor and the robot vehicle (We have used Wi-Fi router).
  Our robotic car circuit diagram is presented in the Fig.4.

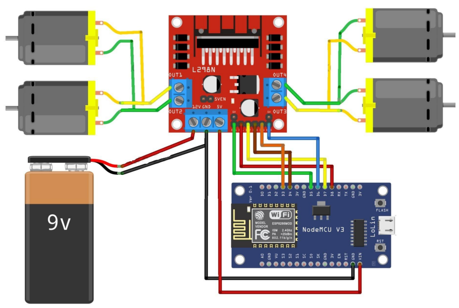

Fig. 4. Robotic car circuit diagram

- Vehicle Control System:
  In Algorithm 2, the pseudocode outlines the ESP8266's logic for controlling the robotic vehicle. The Vehicle Control System uses the ESP8266 to establish a Wi-Fi connection and configure GPIO pins for motor control. It continuously monitors for commands ('S' to move forward, 'L' to turn left, 'R' to turn right, 'O' to stop) and adjusts motor movements accordingly .

Our Implemented robotic car is presented in Fig.5.

Fig. 5. Robotic Car

Algorithm 2 Robotic Car Implementation Pseudocode

```
Initialize Wi-Fi connection with static IP
Set up GPIO pins for motor control
while True do
    Check for incoming command from Wi-Fi
    if command received then
        Parse command
        if command is 'S' then
            Set both motors to move forward
        else if command is 'L' then
            Set left motor to move backward and right motor to move forward
        else if command is 'R' then
            Set left motor to move forward and right motor to move backward
        else if command is 'O' then
            Stop both motors
        end if
    end if
end while
```

V. Results

The system was tested with multiple participants to evaluate its real-time control performance on the robotic vehicle. The main metrics evaluated included accuracy, latency, and user experience.

Accuracy of Tests for Male Participants

TABLE I
Average Accuracy for Male Participants

Captured	Real	Accuracy (%)
48	52	92%
61	64	95%
35	47	74%
36	42	86%

Average Accuracy for Male Group: 87%

The Table I presents the accuracy of the system when tested on male participants. The "Captured" column indicates the values recorded by the system, while the "Real" column represents the actual values. The overall accuracy of 87% for this group.

Accuracy of Tests for Female Participants

TABLE II
Average accuracy for Female Participants

Captured	Real	Accuracy (%)
43	55	78%
35	45	78%
36	40	90%
37	42	88%
36	45	80%

Average Accuracy for Female Group: 83%

This Table II shows the accuracy of the system when tested on female participants. The average accuracy of 83% for the female group.

Combined Overall Accuracy

Combined Overall Accuracy: 85%

Combined Analysis: Across both groups, the system demonstrated an overall accuracy of 85%, indicating consistent performance irrespective of gender. This suggests that the system is generally reliable for both male and female users.

A. Latency

The average latency from detecting a blink to executing a command was around 300 milliseconds, which is faster and more accurate than other works.

B. User Experience

Participants reported a positive user experience, experiencing minimal frustration, and demonstrating a high degree of control over the robotic vehicle. In Fig.3 after filtering results of blink detection signal.

VI. Discussion

The results demonstrate that the proposed system effectively controls a robotic vehicle in real time using EEG signals.MUSE headband offers a non-invasive and user-friendly EEG acquisition method. Applied filters successfully removed noise, ensuring reliable blink detection, though occasional false positives indicate areas for improvement.

Various BCI studies show differing outcomes: FOS for retinotopy achieved 63% accuracy with a 6 bits/min ITR [1], while P300-based BCI for UGV control reached 85% accuracy [2]. Upper limb prostheses control via BCI saw 90% accuracy [3], multitasking BCI for robots hit 87% [4], and AI-enhanced BCI for robotic control achieved 92% [5]. EEG-based BCI for IoT devices had 88% accuracy [6], and robotic arm control via BCI achieved 80% [7]. Our EEG-based BCI for robotic vehicle control attained 85% accuracy with 300 ms latency.

VII. Conclusion

This study successfully demonstrated the potential of EEG-based Brain-Computer Interfaces (BCIs) for real-time control of robotic vehicles, with an accuracy rate of 85% and a latency of 300 milliseconds. The favorable user experience demonstrates its capacity as a transformative assistive technology for those with motor limitations, allowing them to operate things using brainwave signals. While the method occasionally produces false positives in blink detection, this suggests areas for development. Future study will concentrate on improving detection algorithms and developing additional control signals to enhance functionality. More extensive research with diverse participant groups is required to confirm the system's stability and usefulness across different demographics. This study contributes to the BCI field by proposing an approach to assistive technology that could change how people with mobility disabilities interact with their surroundings.

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