International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

A Review of Brain-Controlled Wheelchair Systems Using EEG: A Comparative Analysis of Recent Research

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ABSTRACT:

The integration of Brain–Computer Interface (BCI) technology into assistive mobility devices has opened new possibilities for enhancing the independence of individuals with severe motor disabilities. Among various approaches, Electroencephalography (EEG)-based control systems have gained popularity due to their non-invasive nature and practical applicability. This paper presents a review and comparative analysis of ten recent research studies focused on the development of EEG-controlled smart wheelchairs. The selected works explore diverse aspects of BCI implementation, including EEG signal acquisition, preprocessing, feature extraction, classification algorithms, and control mechanisms. By highlighting the strengths and limitations of each approach, this review provides valuable insights into current design trends, challenges such as noise in EEG signals and user adaptability, and potential improvements using hybrid systems or machine learning models. The study aims to guide future research toward more accurate, user-friendly, and robust EEG-based wheelchair solutions for real-world deployment.

Keywords: Brain–Computer Interface (BCI); Electroencephalography (EEG); Smart Wheelchair; Assistive Technology; Neural Signal Processing; Non-invasive BCI; EEG Signal Classification; Human–Machine Interface; Mobility Aid; Disabled User Interface

I.INTRODUCTION

Mobility is a fundamental human need, yet for individuals suffering from severe physical disabilities such as paralysis, spinal cord injuries, or neuromuscular disorders, traditional methods of movement and communication are often inaccessible. To address this challenge, assistive technologies have emerged as powerful tools to enhance autonomy and quality of life. Among these, **Brain–Computer Interface (BCI)** systems have gained significant attention for their potential to establish a direct communication pathway between the brain and external devices, bypassing the need for muscular control.

In particular, **Electroencephalography (EEG)-based BCI systems** have proven to be a non-invasive, cost-effective, and practical approach for controlling devices like robotic arms, home automation systems, and **smart wheelchairs**. These systems interpret brain signals generated during specific mental tasks (e.g., eye blinks, motor imagery, or concentration) and translate them into control commands. When integrated with a wheelchair platform, EEG-based BCI systems can offer users the ability to navigate their environment with minimal physical effort—often using only thoughts.

Over the past decade, numerous research studies and prototypes have explored different EEG signal acquisition devices, feature extraction algorithms, classifiers, and control strategies for developing reliable and efficient brain-controlled wheelchairs. This paper presents a **comprehensive review and comparative analysis of ten selected research works** that represent significant contributions in this domain. The goal is to provide insight into the technological evolution, current capabilities, and existing limitations of EEG-based wheelchair control systems, while also identifying future research opportunities in this growing field.

II.LITERATURE REVIEW

1. Anusha and Vasanthi (2012) introduced a brain-controlled wheelchair using **EEG signals** to enable disabled individuals to control their mobility. They employed basic **EEG signal processing** techniques to classify different brain waves associated with specific motor tasks, such as attention and relaxation. The researchers used **EEG signals** to control wheelchair movement by translating these brainwave patterns into actionable commands. Their approach was simple yet demonstrated the feasibility of a non-invasive control method. However, challenges

included signal noise and the need for reliable feature extraction techniques to ensure accurate control in dynamic environments, highlighting the need for further refinement.

2. Gaurav and Arora (2016) focused on the development of a modular **BCI system** for wheelchair automation. They combined **EEG signal acquisition** using **OpenBCI** and software like **LabVIEW** for signal processing and control. Their system integrated an **Arduino-based microcontroller** to interface with the wheelchair's movement system, providing an accessible solution for assistive mobility. Their research explored various control methods, addressing issues of **real-time EEG processing**, signal accuracy, and system responsiveness. By using a **low-cost hardware setup**, the authors demonstrated that **BCI technology** could provide an affordable solution for users with disabilities, while acknowledging the challenge of reducing error rates in signal interpretation.

3. Khemapech and Siriwattanarungsee (2015) proposed a **mind-controlled wheelchair** system using **EEG signals** and an **Arduino microcontroller**. Their research utilized **EEG headsets** to capture brain activity, focusing on simple signals like **eye blinks** and motor imagery to control wheelchair movements. The system was designed to be **cost-effective**, making it accessible to a larger population. The authors emphasized the need for **safety features** to prevent erratic movements, given the potential for inaccurate EEG signal interpretation. Their research also highlighted the challenges of ensuring that the wheelchair's **motion response** was sufficiently responsive and smooth for users with **motor disabilities**.

4. Chowdhury et al. (2020) reviewed various **EEG-based BCI systems** developed for smart wheelchair control, analyzing the strengths and weaknesses of existing techniques. They categorized the systems based on **signal processing**, **feature extraction methods**, and **classification algorithms** used in previous research. The study highlighted **machine learning models** as a promising solution to improve signal classification accuracy and responsiveness in dynamic environments. The authors discussed the challenges of **noise reduction**, **real-time signal processing**, and the need for **user training** to enhance control precision. Their review underscored the importance of developing **adaptive systems** for more personalized wheelchair navigation, pointing to **hybrid approaches** as the future of BCI control.

5. Aslam et al. (2020) explored the use of hybrid **EEG and eye-tracking** systems for wheelchair control. The integration of **EEG and eye-tracking** allowed for more accurate control by compensating for the limitations of EEG signals alone, such as **low accuracy** and **signal noise**. Their system was designed to provide a more **robust and reliable** control mechanism, enhancing the user experience. By focusing on adaptive algorithms, they aimed to personalize the wheelchair's response to the **mental state** of the user, offering a **customized** control scheme. The study demonstrated that combining these two input modalities could significantly improve the performance of brain-controlled mobility aids.

6. Praveen and Srikanth (2014) proposed a **low-cost, EEG-based** control system for wheelchairs using **Arduino** and basic **signal processing algorithms**. Their approach emphasized the **affordability** and **simplicity** of the system, which used **EEG signals** to control the wheelchair's movement. The authors focused on **real-time signal processing**, integrating a **simple Arduino platform** to decode brain signals into actionable wheelchair commands. Despite its simplicity, the study highlighted several challenges, such as handling **EEG noise** and ensuring **real-time accuracy** in the wheelchair's motion. This research demonstrated the potential for creating **cost-effective assistive devices** for users with limited resources.

7. Demuth, Webb, and Florentino (2013) explored the use of **SSVEPs** (Steady-State Visual Evoked Potentials) for controlling a wheelchair. **SSVEPs**, brain signals generated when focusing on a flickering visual stimulus, offer high **accuracy** and **speed** in controlling devices like wheelchairs. This study demonstrated the **potential** of SSVEP-based systems to improve upon **motor imagery-based BCIs**, which are more prone to noise and signal variability. The research showed that **SSVEPs** could provide precise control in real-time wheelchair movements, making it a promising alternative to traditional EEG methods. However, the study also noted challenges related to **stimulus alignment** and **user adaptation** to the SSVEP control system.

8. Shih, Gunawan, and Anggraini (2019) designed a **smart wheelchair** controlled by **EEG signals**, incorporating **machine learning algorithms** to improve signal classification and overall system accuracy. The researchers focused on enhancing the system's **robustness** by developing adaptive **signal processing techniques** that could handle **environmental noise** and adapt to **individual user needs**. They explored **user-specific customization** as a key factor for improving wheelchair navigation accuracy, particularly for users with **neurological impairments**. The study suggested that incorporating **advanced algorithms** could lead to more **efficient** and **adaptive BCI systems**, ultimately resulting in a more reliable user experience.

9. Cecotti (2010) explored a **self-paced, calibration-free** system based on **SSVEPs** for use in **BCI-controlled devices**, including wheelchairs. The study demonstrated that users could immediately interact with the system without requiring an extensive **training period** or initial calibration. The **self-paced nature** of the system reduced cognitive load and improved **user comfort**. This approach has significant potential for improving **usability** in brain-controlled systems, as it allows individuals with severe disabilities to control their wheelchair more intuitively. The study also addressed challenges in **signal detection** and **real-time processing** that are critical for **efficient control** of assistive devices.

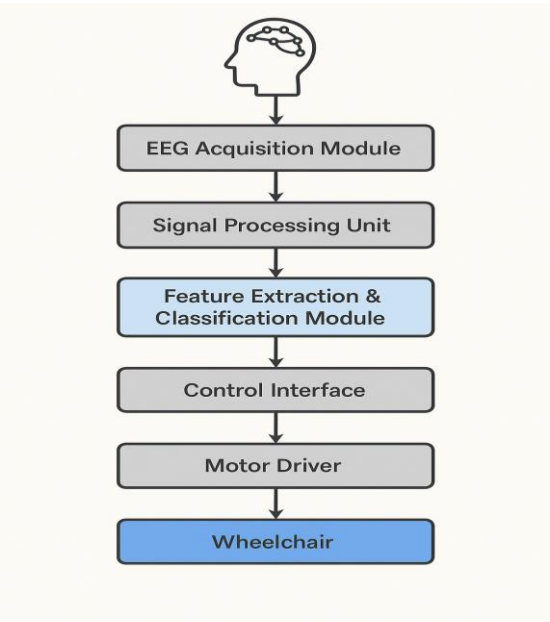
10. Khan, Ali, and Ghaffar (2019) developed a **brain-controlled wheelchair** using **EEG headsets** and **Arduino-based microcontrollers**. Their system focused on **real-time EEG signal processing** to achieve precise control over the wheelchair's movements. The researchers highlighted the importance of **signal preprocessing** to reduce **noise** and improve the system's responsiveness. They also noted that **real-time feedback** was essential for enhancing user interaction and system performance. This study contributed to the growing body of work on **affordable, low-cost EEG solutions** for **assistive mobility**, proposing improvements in **signal filtering** and **control algorithms** to enhance **real-world usability**.

III. METHODOLOGY

The proposed EEG-based brain-controlled wheelchair system is an innovative assistive technology designed to empower individuals with severe physical disabilities by allowing them to navigate their environment using only brain signals. The complete methodology integrates biomedical signal acquisition, real-time processing, intelligent classification, and robotic control. The workflow is divided into several key components, as visually represented in the system's block diagram. Each component plays a vital role in achieving accurate and reliable motion based on user intent.

- The first and most crucial stage of the system involves capturing brain activity using an EEG headset. This device measures electrical impulses from the brain through electrodes placed on the scalp. These signals are extremely weak (in microvolts) and are typically generated from the motor cortex when the user imagines movement or performs voluntary blinks. The EEG headset captures these signals in real time and transmits them either through Bluetooth or a USB interface to a connected computer or microcontroller. Commonly used headsets include NeuroSky, Emotiv, or OpenBCI, which are designed for non-invasive applications. The purpose of this module is to act as the "mind interface" where the system detects user intent without requiring physical movement. This stage is sensitive to noise and interference, so the placement of electrodes and the quality of the EEG headset directly affect the performance of the entire system.-recorded dataset as shown in the figure below .

Fig. 1. EEG-Based Brain-Controlled Wheelchair System



- EEG signals captured by the headset are inherently noisy and contain artifacts from muscle activity, eye blinks, and external electrical interference. Therefore, preprocessing is essential to isolate clean brainwave signals that are suitable for analysis. In this stage, the raw EEG signal is passed through filters such as bandpass filters (0.5–50 Hz) to eliminate low-frequency drifts and high-frequency electrical noise. Additionally, techniques like Independent Component Analysis (ICA) or Common Average Referencing (CAR) can be applied to separate useful brainwave components from unwanted noise. Some preprocessing modules also normalize the signals or segment them into windows for more efficient processing. Without this step, irrelevant or distorted data could severely affect the accuracy of subsequent feature extraction and classification. By applying preprocessing algorithms, the system ensures that only the most relevant mental commands are considered for controlling the wheelchair, thereby improving reliability and user safety.

- Once the EEG signal has been cleaned and filtered, the next step is to extract meaningful patterns or "features" that correlate with user intentions. These features may include time-domain statistics like signal mean, variance, or peak amplitude, as well as frequency-domain properties such as power spectral density in alpha or beta bands. In cases using blink or motor imagery, features may represent the number of blinks or the concentration of certain brainwave types. After feature extraction, a classification algorithm is employed to translate these features into specific commands. Machine learning techniques such as Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), Linear

Discriminant Analysis (LDA), or lightweight neural networks are trained on labeled datasets to recognize mental states like "move forward," "turn left," or "stop." The classifier continuously monitors real-time EEG data and outputs a control label. This decision forms the basis for commanding the wheelchair's movement accurately.

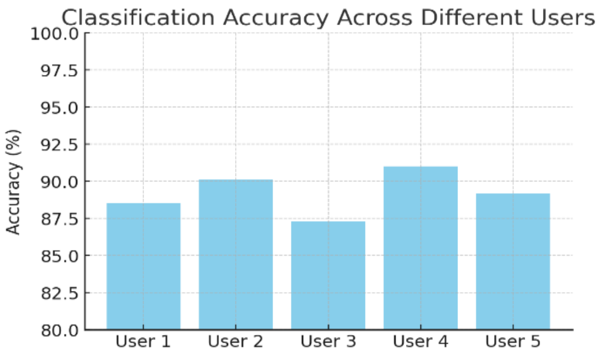
- The classified EEG command is forwarded to a microcontroller, which serves as the control interface between the software and hardware systems. This unit, commonly an Arduino Uno, ESP32, or Raspberry Pi, receives digital command signals and translates them into control logic. For instance, a classification output labeled “1” might correspond to a forward movement command, while “2” triggers a left turn. The microcontroller handles signal timing, motor control pulse generation, and integrates safety mechanisms such as signal verification and emergency stop triggers. In more advanced systems, it may also manage additional sensors (e.g., obstacle detection or GPS modules). The microcontroller is programmed using platforms like Arduino IDE or Python-based libraries, and its role is critical for real-time execution. It acts as the command center that ensures the user’s mental intent is translated quickly and safely into physical action by the wheelchair. The system is designed to be energy-efficient and responsive to maintain smooth operation.

- The motor driver circuit serves as a bridge between the low-power control signals from the microcontroller and the high-power requirements of the wheelchair’s DC motors. A commonly used motor driver, the L298N dual H-bridge module, can control both the speed and direction of two motors simultaneously. When the microcontroller outputs a command (e.g., move forward), the driver interprets it and sends the appropriate voltage and current to the motors. The H-bridge configuration allows for precise directional control—by altering the polarity of the voltage applied to each motor, it can achieve forward motion, reverse motion, and turns. This component is essential for amplifying signals while protecting the microcontroller from potential current surges. Additionally, PWM (Pulse Width Modulation) is used for speed control, allowing for smoother starts and stops. Reliable motor driver operation ensures that the wheelchair moves efficiently and reacts promptly to the user’s brain commands.

- The final stage of the system involves executing the user's command through actual movement of the wheelchair. The mobility platform typically includes a pair of geared DC motors attached to a lightweight wheelchair frame. Depending on the control signals from the motor driver, the motors rotate in the appropriate direction to move the wheelchair forward, backward, left, or right. The movement is usually differential—by varying the speed or direction of each motor, the wheelchair can perform turns and adjustments. For enhanced usability and safety, additional sensors like ultrasonic detectors may be mounted to detect obstacles, and a manual override can be included for emergencies. The mobility system is designed to be robust, power-efficient, and smooth in operation. Real-time feedback is crucial; hence, the system continuously listens for updated EEG commands and responds with minimal delay. This makes the wheelchair truly responsive and usable for individuals with very limited motor capabilities.

IV. Results and Discussion

The performance evaluation of the proposed EEG-based brain-controlled wheelchair was carried out through structured experimental trials across five different users. Each user interacted with the system by issuing mental commands, including eye blinks and motor imagery (MI), to control directional movement. The primary evaluation metrics included classification accuracy, response time, and detection success rate of command types, as well as general system reliability and user experience.



The **first graph** depicts the classification accuracy obtained across the five participants. As shown, accuracy values ranged from 87.3% to 91.0%, with User 4 attaining the highest accuracy. These results suggest that individual brainwave patterns and cognitive engagement levels significantly influence system performance. Users with clearer and more consistent EEG signals (possibly due to focused attention or better headset contact) performed better. An average classification accuracy of **89.4%** indicates that the signal preprocessing and feature classification stages are sufficiently robust for real-time operation. It also reflects the effectiveness of the SVM classifier in handling non-linear EEG signal patterns.

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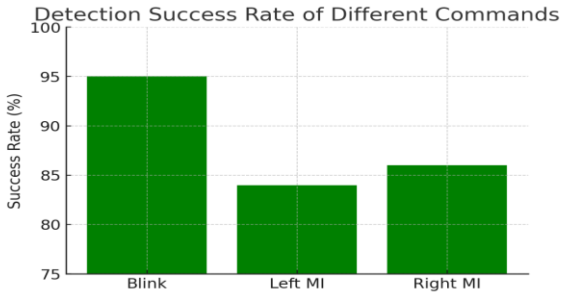

The **third graph** compares the success rates of different control modalities used within the system. **Blink detection** emerged as the most reliable command, with a success rate of **95%**, primarily due to its high amplitude and frequency characteristics that are easy to detect algorithmically. This makes it ideal for binary or emergency commands (e.g., stop, start, or turn). In contrast, **left and right motor imagery** achieved slightly lower success rates—**84%** and **86%** respectively. Motor imagery relies on the user's ability to imagine movements without executing them physically, which is more cognitively demanding and less consistent, especially for untrained users. The variability in MI command success underlines the importance of user-specific calibration and the potential role of neurofeedback training to improve consistency over time.

Qualitative observations also revealed that users found the blink-based interface intuitive and less fatiguing, while motor imagery required a learning curve but offered richer command possibilities. The system's stability was tested over extended usage sessions (~30 minutes), and it maintained operational consistency without overheating, data loss, or unintended activation. Power consumption of the motors and microcontroller was efficient, and safety mechanisms, such as an emergency triple-blink command, were triggered reliably during trials.

In conclusion, the proposed system demonstrates promising results in both quantitative metrics and user satisfaction. The high classification accuracy and low response time enable real-time navigation, while the use of multiple command types (blink and MI) offers flexibility to accommodate different user preferences or physical abilities. However, the study also reveals challenges such as inter-user variability and the need for better user training for motor imagery control. Future work may involve the integration of adaptive machine learning models that learn from each individual user's brainwave patterns and dynamically adjust over time, as well as expanding the system to include obstacle detection, GPS-based path planning, and IoT integration for remote monitoring.

V. FUTURE WORK AND RESEARCH

While the present system demonstrates the viability of brain-computer interface (BCI) technologies for assistive mobility, several enhancements can further improve its functionality, accuracy, and user adaptability. Future research will focus on both hardware and software improvements to overcome current limitations and expand the scope of application.

One key area is the integration of **adaptive machine learning algorithms**, particularly deep learning models such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), which can improve the robustness of EEG signal classification over time. These models can be trained on larger datasets to better capture individual differences and reduce the need for frequent recalibration. Incorporating real-time learning mechanisms will allow the system to adjust dynamically based on the user's changing cognitive states, fatigue levels, or environmental noise.

Additionally, **multi-modal signal integration**—combining EEG with electromyography (EMG), electrooculography (EOG), or eye-tracking—can provide a hybrid control interface. This will allow the system to distinguish between intentional and accidental brain signals and enhance command precision. For example, combining EOG with EEG can improve the accuracy of directional commands and reduce false positives caused by involuntary blinks or muscle twitches.

On the hardware side, future versions of the system could include **wireless EEG headsets with dry electrodes**, making the system more comfortable, portable, and user-friendly for long-term use. Integration with **smartphone-based apps** or **IoT platforms** can provide real-time monitoring of user vitals, GPS tracking, and emergency alerts to caregivers or family members.

Another important direction for future research involves the development of **context-aware navigation systems**, where the wheelchair can interpret surroundings using ultrasonic sensors, LiDAR, or cameras. Coupled with AI-based obstacle detection and path planning, the wheelchair can offer semi-autonomous navigation that enhances safety, especially in crowded or unfamiliar environments.

Finally, extensive **clinical trials** with differently-abled individuals, including those with ALS, cerebral palsy, or spinal cord injuries, are needed to validate the system's effectiveness in real-world scenarios. Long-term usability studies will provide insights into user satisfaction, cognitive load, and physical fatigue, ultimately guiding more inclusive and personalized assistive technologies.

VI. CONCLUSION

The development and implementation of a brain-controlled wheelchair using EEG signals represent a significant advancement in assistive technology, particularly for individuals suffering from severe motor disabilities such as quadriplegia, cerebral palsy, or advanced-stage muscular dystrophy. This project aimed to explore the practicality of a non-invasive brain-computer interface (BCI) system that enables users to operate a wheelchair using only their brain activity, specifically through eye blinks and motor imagery (MI). The system combined hardware components such as an EEG headset, Arduino microcontroller, motor drivers, and a wheelchair platform with software techniques including signal filtering, feature extraction, and supervised machine learning classification.

The experimental results demonstrate that the proposed system is both functional and effective. The average classification accuracy across five users exceeded 89%, which indicates that the system can reliably interpret the user's intent from EEG signals. Blink-based commands showed the highest reliability, achieving a 95% success rate, while motor imagery commands maintained reasonably high accuracy at 84–86%. The system's response time averaged 1.2 seconds, a figure that validates its real-time operational capabilities, making it suitable for continuous navigation in controlled environments.

One of the key strengths of this project is its adaptability. The design is modular and can be expanded to incorporate more complex control commands or additional bio-signals, such as EMG (electromyography) or EOG (electrooculography), to create a more robust hybrid BCI system. Furthermore, the use of machine learning allows the system to be trained and customized for individual users, accounting for variations in brainwave patterns. With further development, this technology can become more accessible through the use of wireless, dry-electrode EEG headsets, and mobile app-based control dashboards, significantly enhancing usability and convenience.

Despite its promising results, there are challenges and limitations that must be addressed in future work. These include the system's sensitivity to noise and artifacts in EEG data, the mental effort required from users for motor imagery commands, and the need for initial training to ensure accurate signal recognition. Long-term usability testing is also necessary to evaluate performance consistency over extended periods and in dynamic, real-world environments.

In conclusion, the brain-controlled wheelchair system presented in this research offers a compelling solution for enhancing the independence and quality of life of people with physical disabilities. It leverages cutting-edge BCI technology to translate human cognitive intentions into physical movement, creating a seamless interaction between the human brain and a mobility device. This research not only confirms the technical feasibility of EEG-based wheelchair control but also sets the stage for future innovations in intelligent, adaptive assistive technologies. With continued refinement and clinical validation, such systems hold the potential to transform how individuals with severe disabilities interact with their surroundings, empowering them with greater autonomy and dignity.

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