Using EEG Signal for Smart Health: An Overview

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***Abstract*—This survey paper aims to provide an overview of the current state of EEG (Electroencephalography) signal technology as it relates to people with disabilities. It will highlight the various methods and techniques employed, discussing their advantages and disadvantages. The paper will also examine the applications of EEG technology in assisting individuals with disabilities, specifically focusing on Brain-Computer Interfaces (BCIs) and assistive device control. By understanding the current state of EEG signal technology, we can identify the opportunities and challenges involved in utilizing this technology to improve the lives of people with disabilities.**

***Keywords*—EEG, assistive technologies, brain-computer interface, BCI**

I. Introduction

People with disabilities (PWD) represent a significant portion of the global population, and understanding the statistics surrounding disabilities is crucial for addressing their needs and promoting inclusivity. According to the World Health Organization (WHO), 15% of the world's population, or over 1 billion people, are estimated to be living with some form of disability [1]. Disabilities can result in physical limitations and health challenges. This may include difficulties with mobility, coordination, strength, endurance, and self-care tasks. Individuals may require assistive devices such as wheelchairs, crutches, or hearing aids to enhance their independence and functionality.

Many individuals with disabilities face obstacles in accessing physical environments, public transportation, buildings, educational institutions, and other public facilities. This lack of accessibility can limit their participation in various activities and restrict their freedom of movement [1]. The cost of disability-related services, assistive devices, and healthcare can be a significant barrier. Additionally, individuals with disabilities may face income disparities, lower employment rates, and financial challenges due to limited job opportunities or discrimination. EEG signal technology can greatly improve the lives of people with disabilities in various ways.

EEG-based assistive devices, such as brain-controlled prosthetics and communication systems, enable people with severe physical disabilities to regain independence. Elderly people can be considered a major focus since more than 46% of those ages 60 and above have some form of disability. This population is expected to reach approximately 2 billion by the year 2050 [2]. By interpreting EEG signals, these technologies allow users to control external devices using their brain activity, improving their quality of life and reducing inequalities. Assistive technologies have emerged as powerful tools in empowering PWD and enabling their full participation in various aspects of life. Recognizing the potential of EEG signal based assistive technologies and ensuring their availability, affordability, and widespread implementation are crucial steps toward building a more inclusive and equitable world, where the well-being of all individuals, including those with disabilities, are realized.

A. Background

The foundations for EEG technology began in the late 19th century when scientists such as Richard Caton and Hans Berger discovered that the human brain produces electrical activity. In the 1920s, Berger recorded human brain waves using an early EEG device [3]. From there, EEG found practical applications as a diagnostic tool for epilepsy. The introduction of electrode caps simplified electrode placement, and amplifiers were used to enhance signal detection and analysis, making EEG technology more practical for clinical and research purposes. In the 1970s, researchers began exploring the potential of EEG-based BCIs, initially focusing on simple binary control tasks. In 1977, a study by Vidal demonstrated that individuals could control a computer cursor by modulating their brain activity [3]. In the 1990s, communication aids and neuroprosthetic devices

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started to emerge. Research into those devices has continued to progress, leading to more sophisticated and accurate systems. Signal processing techniques and machine learning algorithms have greatly enhanced the capabilities of EEG technology, allowing for more accurate and efficient detection, classification, and interpretation of EEG signals [3].

Over time, EEG technology has expanded beyond epilepsy to encompass a range of disabilities and conditions. It has been applied in rehabilitation to assist individuals recovering from stroke, traumatic brain injury, or cognitive impairments. Today, EEG technology continues to evolve, with ongoing research focused on improving signal quality, enhancing user experience, developing more advanced algorithms, and exploring new applications. The combination of EEG with other technologies, such as virtual reality and robotics, holds further promise for improving the lives of people with disabilities.

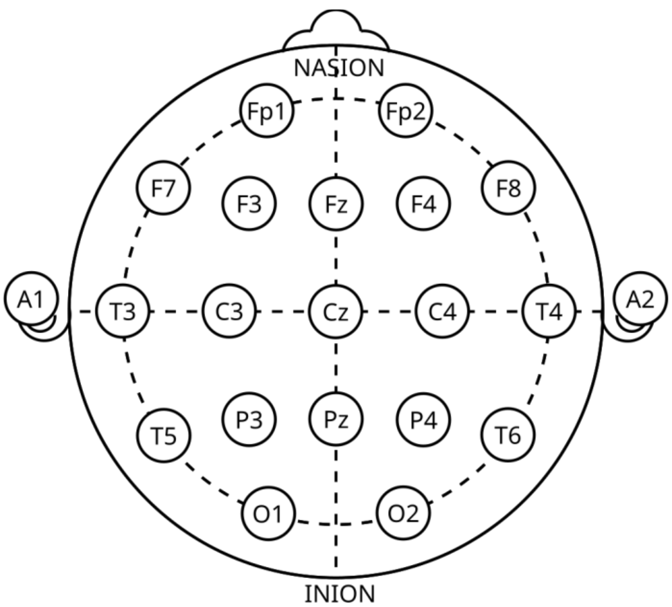

Fig. 1. A standard diagram labelling positions on the scalp for the placement of electrodes.

B. Importance

EEG technology research has the potential to significantly enhance the quality of life for people with disabilities. By developing innovative applications and assistive devices, researchers can provide individuals with disabilities with new means of communication, mobility, and independence, empowering them to actively participate in society and lead more fulfilling lives [4]. EEG research contributes to the development of assistive technologies that enable individuals with disabilities to overcome limitations and engage with the world. This includes devices such as BCIs, neuroprosthetics, and communication aids, which harness EEG signals to interpret intentions and enable control of external devices. Advancements in EEG technology research will lead to more accurate, reliable, and user-friendly assistive devices.

EEG-based research aids in neurorehabilitation, helping individuals with disabilities recover lost motor or cognitive functions [5]. By understanding the brain's plasticity and employing techniques such as neurofeedback, researchers can develop personalized rehabilitation protocols that optimize recovery and promote neural reorganization [5]. This research enables individuals to regain independence and improve their functional abilities. This also contributes to the early detection and intervention of neurological conditions and disabilities. By studying EEG patterns and identifying abnormal brain activity, researchers can develop diagnostic markers that facilitate early identification of conditions such as epilepsy, sleep disorders, or cognitive impairments. Early detection allows for timely interventions, leading to better treatment outcomes and improved management of disabilities.

EEG signal technology research enables personalized approaches to healthcare for PWD. By analyzing individual EEG profiles, researchers can create treatment plans and therapies for specific needs, maximizing their effectiveness. Personalized medicine ensures that interventions are customized, efficient, and focused on addressing the unique challenges faced by each person with a disability. EEG research contributes to the broader scientific understanding of the brain and its functions. By investigating EEG signals, brainwave patterns, and neural correlates of disabilities, researchers gain insights into the underlying mechanisms of various conditions [4]. This knowledge helps refine diagnostic criteria, improve treatment strategies, and inform the development of novel therapeutic approaches for PWD.

This research plays a vital role in promoting societal inclusion and equality for people with disabilities. By creating innovative solutions and reducing barriers, researchers can help bridge the gap between individuals with disabilities and their non-disabled peers. Accessible and user-friendly EEG-based technologies ensure that people with disabilities have equal opportunities, empowering them to participate fully in education, employment, and social activities. In summary, EEG signal technology research is critically important for the world, particularly for PWD, as it leads to advancements in assistive technology, rehabilitation, early detection, personalized medicine, scientific knowledge, and societal inclusion [6]. By continuing and developing EEG research, we can continue to improve the lives of individuals with disabilities and promote a more inclusive and equitable society.

C. The Need and Statistics

Communication assistance is needed for individuals with certain disabilities, such as severe motor impairments, where people may lose their ability to communicate effectively. EEG-based BCIs provide a means for these individuals to communicate by translating their brain activity into commands. This technology can be crucial for maintaining social interaction and independence. Moreover, control of assistive devices by people with disabilities often requires assistive devices like prosthetics, wheelchairs, or environmental control systems. EEG signals can be used to control these devices directly, bypassing the need for physical interaction [5]. This enables individuals with limited or no limb mobility to independently perform daily tasks, enhancing their autonomy.

Additionally, EEG technology is employed in neurorehabilitation to aid in the recovery of motor function after stroke, spinal cord injury, or traumatic brain injury [5]. By monitoring brain activity, therapists can tailor rehabilitation protocols to everyone's needs, optimizing treatment outcomes. Lastly, the need to monitor sleep disorders and epilepsy is a key tool for EEG devices as it helps healthcare professionals assess brain activity during sleep or detect abnormal electrical patterns associated with seizures [7]. This data assists in the accurate diagnosis and treatment of these conditions.

The Centers for Disease Control and Prevention (CDC) report that 27 percent of American adults have some type of disability. 12.1 percent of U.S. adults have a mobility disability, 12.8 percent have a cognition disability, 7.2 percent have independent living disability, 6.1 percent are deaf or have some form of hearing impairment, 4.8 percent have a vision disability, and 3.6 percent have a self-care disability [8]. Due to these statistics, EEG-based BCIs have gained significant research attention. For example, studies on stroke rehabilitation using EEG-based BCIs have shown promising results in improving motor function and recovery outcomes [5][11][24]. Extensive research continues to explore novel applications and improve diagnostic accuracy [5].

It's important to note that the field of EEG signal technology is continually evolving, with ongoing research and technological advancements. These statistics and insights provide a glimpse into the need and potential of EEG technology for people with disabilities, but further developments are expected to expand its applications and impact in the future.

II. Technical Challenges

A. Neural Rehabilitation

In this section we discuss an overview of some technical challenges of developing EEG devices for smart health. When developing advanced neural rehabilitation and intelligent interaction technology to assist people with disabilities using EEG, there are several technical challenges to overcome. One of them being signal quality and calibration [9]. EEG signals can be susceptible to noise and artifacts, particularly in individuals with disabilities. Ensuring good signal quality is crucial [9]. Calibration procedures need to account for individual differences, variations in electrode placement, and changes over time. Another major technical challenge when developing this type of technology can include individual variability and adaptation. When creating adaptive systems, it is essential to take account of individual variability, adapt to changes in neural signals, and learn from user feedback. Machine learning techniques can help in personalizing the rehabilitation and interaction experience.

Additionally, the incorporation of user training and learning is essential to understand this type of technology. Training individuals with disabilities to use EEG-based assistive technologies effectively requires careful consideration. People with disabilities may face challenges in understanding and executing the required mental tasks or motor imagery. Developing user-friendly training protocols, providing feedback, and ensuring user engagement is vital for successful adoption and effective use. Overall, addressing these technical challenges requires collaboration between researchers, engineers, clinicians, and end-users to be able to effectively assist people with disabilities using EEG [9].

B. Brain Activity Monitoring

There is a need for brain activity monitoring with EEG, one reason being due to its non-invasiveness. EEG is a non-invasive technique that allows for the measurement of electrical activity in the brain through electrodes placed on the scalp, making it useful and suitable for a wide range of applications, including clinical, research, and personal use [10]. It provides a safe and relatively low-cost method for monitoring brain activity compared to invasive procedures, such as intracranial electrodes. Furthermore, EEG-based brain activity monitoring is widely used in clinical settings for diagnosing and monitoring various neurological disorders. It aids in identifying abnormal brain wave patterns associated with epilepsy, sleep disorders, brain injuries, and other neurological conditions. EEG monitoring can provide critical information for guiding treatment decisions and assessing updates on neurological disorders [11]. Using EEG allows clinicians to monitor real-time results. This type of monitoring is valuable in situations where quick assessment and intervention are necessary, such as during epilepsy seizures, anesthesia monitoring, or intraoperative monitoring. Moreover, EEG-based brain activity monitoring is fundamental for developing and implementing BCIs. BCIs translate brain signals captured by EEG into control commands for external devices, enabling individuals to interact with their environment or control assistive technologies using their thoughts and potentially enhancing the quality of life for people with severe disabilities. EEG-based brain activity monitoring can also be utilized in rehabilitation settings and neurofeedback training, helping individuals with neurological conditions or injuries such as stroke or traumatic brain injury to engage in personalized rehabilitation programs [5]. Neurofeedback training enables those in need to self-regulate and improve specific brain patterns associated with motor control, attention, or relaxation. By providing a non-invasive, real-time, and cost-effective method for measuring brain activity, EEG-based brain activity monitoring fulfills critical needs in medical diagnosis, research, rehabilitation, and personal wellness.

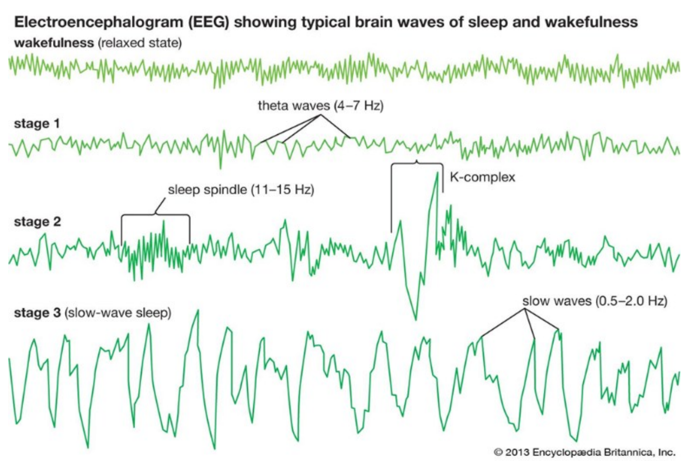

Fig. 2. Examples of human brain waves in various classes and states [31].

C. EEG Wheelchairs

Several factors can contribute to inaccuracies in EEG wheelchairs. One of the main factors that can affect the accuracy of EEG-based control systems for wheelchairs includes noise and artifacts. EEG signals can be contaminated by various types of noise and artifacts, such as muscle activity (electromyography), eye blinks and eye movements (electrooculography), or environmental interference. These unwanted signals can interfere with the accurate detection and classification of brain signals associated with the user's intentions, leading to inaccuracies in wheelchair control [9]. Furthermore, the placement of EEG electrodes is critical for obtaining reliable signals. If electrodes are misaligned or not in direct contact with the scalp, it can affect the quality of recorded EEG signals and therefore distort the underlying brain activity. Individual variability is also another common factor considering scalp morphology, skull thickness, and the distance between the brain and the electrodes. These differences pose challenges in developing generic EEG-based control systems that accurately translate the user's intentions into wheelchair commands. Moreover, extracting relevant information from EEG signals and accurately classifying the user's intentions can be challenging [9]. Different mental tasks or motor imagery used for control commands may not produce distinct or consistent patterns in EEG signals [12]. Complex signal processing techniques and advanced machine learning algorithms are required to overcome these challenges and improve accuracy. Overall, advancements in signal processing algorithms, electrode technologies, user-specific calibration methods, and adaptive learning approaches are crucial to minimize inaccuracies and improve the overall accuracy and reliability of EEG wheelchairs.

III. Overview of Various Techniques

A. *EEG-Based BCI System*

Some of the components of an EEG-based BCI system for people with disabilities include the following: EEG signal acquisition where the system detects and records the electrical activity of the user's brain; signal processing and feature extraction to enhance signal quality, including filtering, artifact removal, and feature extraction algorithms; classification and decoding where machine learning algorithms or pattern recognition techniques are employed to classify and interpret the extracted features from the EEG signals; and, accessibility and user interfaces where the BCI system is designed to cater to specific needs and abilities of individuals with disabilities [14].

An EEG-based BCI system for people with disabilities has the potential to significantly enhance their quality of life by providing alternative communication and control options. Ongoing research and technological advancements in EEG-based BCIs are aimed at improving their accuracy, usability, and practicality for individuals with diverse disabilities [14].

B. *Smart Consumer EEG Devices*

Smart consumer EEG devices are portable, user-friendly devices that allow individuals to monitor and measure their brain activity using an Analog to Digital Converter (ADC). These devices typically consist of a headband or electrodes that are placed on the scalp to capture electrical signals from the brain. The analog signals generated by the electrodes are then converted into a digital format using an ADC, which enables the signals to be processed and analyzed by software applications or mobile devices [15]. These smart consumer EEG devices often come with accompanying smartphone or computer applications that provide real-time feedback and visualizations of brain activity. Users can monitor various aspects of their brain function, such as relaxation, focus, or stress levels. Some devices even offer meditation guidance or brain training exercises based on recorded EEG data. The integration of ADC technology in these devices is crucial as it allows for accurate and reliable digitization of analog EEG signals. Smart consumer EEG devices provide individuals with a convenient and accessible way to gain insights into their brain activity without the need for professional medical equipment or extensive training.

C. *EEG Devices for Detection and Diagnosis*

EEG devices can be used to detect abnormal electrical discharges in the brain, which can provide valuable information for the diagnosis of various conditions, including cardiac arrest, brain death, cerebral hypoxia, brain tumors, and epilepsy [16]. In a scenario such as a cardiac arrest, the human brain is deprived of oxygen and blood flow, resulting in an abnormal electrical activity pattern. EEG recordings can help identify the absence of brain activity, indicating brain death, or the presence of abnormal electrical discharges associated with ischemia or anoxia. EEG monitoring can assist in determining the prognosis and evaluating the effectiveness of resuscitative efforts. In a case dealing with cerebral hypoxia, where the human brain receives insufficient oxygen, EEG monitoring such as slowing of the EEG rhythm, decreased amplitude, and the appearance of specific patterns can aid in the assessment of the severity and progression of cerebral hypoxia. Lastly, in a scenario with brain tumors, EEG can provide useful information about their location and characteristics. Tumors can cause abnormal electrical discharges or disrupt the normal patterns of brain activity in the surrounding areas. EEG recordings can help identify epileptiform activity, focal slowing, or other abnormal patterns that may indicate the presence of a brain tumor. Overall, EEG devices are used to record and analyze the electrical activity of the brain, providing valuable information for diagnosing and monitoring various neurological conditions [16].

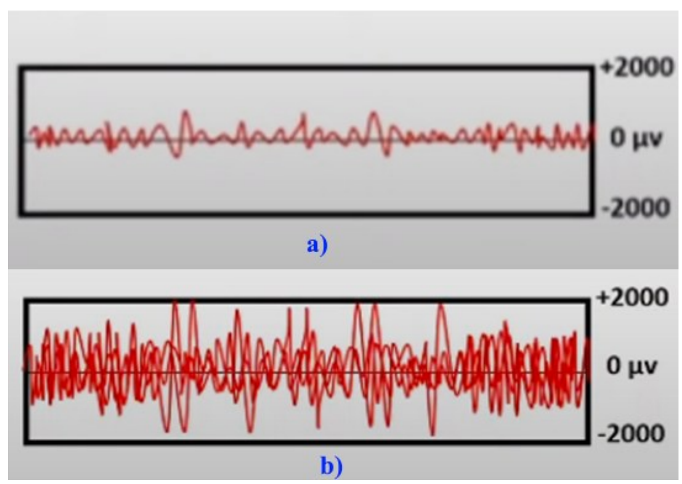

Fig. 3. A comparison of human brain waves showing a healthy individual (a) and an epilepsy patient (b). This shows how EEG can be used for diagnosis and monitoring in epilepsy patients.

D. *Portable BCIs*

Low-cost portable Brain-Computer Interfaces (BCIs) with performance comparable to or even better than conventional BCIs offer several advantages that make them desirable in various applications. One of the many reasons why low-cost portable BCIs with improved performance can serve advantageous includes their accessibility and affordability [17]. Low-cost BCIs make the technology more accessible to a broader range of users. Another reason can include its mobility and flexibility. Users can use them in various settings, including their homes, hospitals, or rehabilitation centers, without being limited by stationary equipment. Moreover, low-cost portable BCIs are often designed with user comfort in mind. The use of lightweight materials, flexible electrodes, and ergonomic designs ensures that the BCI is comfortable to wear for extended periods. This enhances the user experience and promotes long-term usage without discomfort or fatigue. Furthermore, through improved signal quality and processing, technological advancements have led to improved signal quality and noise reduction in low-cost BCIs. This enhances the accuracy and reliability of detecting and interpreting brain signals, resulting in better performance. It's important to note that while low-cost portable BCIs offer many advantages, they may have certain limitations compared to high-end, research-grade BCIs. Factors such as the number of channels, spatial resolution, and specialized functionalities may differ between low-cost and conventional BCIs [17].

E. *EEG and Eye-Tracking for Smart Wheelchair Control*

The control of a smart wheelchair using EEG signals and eye tracking as input modalities allow individuals with limited mobility to operate the wheelchair through their brain activity and eye movements [18]. By processing and analyzing these signals, machine learning algorithms can recognize patterns related to the user's intentions and generate control commands for the wheelchair. The integration of EEG and eye tracking provides a more intuitive and efficient control interface, enhancing user independence and mobility. Ongoing research focuses on improving the accuracy, responsiveness, and usability of this combined modality control system [18].

Eye tracking technology is utilized to monitor the user's eye movements and determine the direction of their gaze. By tracking the position and movement of the eyes, the system can identify the user's intended direction or target location, allowing for intuitive control of the wheelchair based on the user's gaze [20]. Moreover, specific brain patterns or signals associated with motor intention, such as imagining moving forward or turning, can be extracted from the EEG data [15]. Machine learning algorithms are applied to analyze these signals and map them to corresponding wheelchair commands. These systems also require an initial calibration phase where the user's eye gaze and EEG signals are recorded to establish personalized models for intention detection and eye gaze control. This process allows the system to adapt to the user's specific brain activity and eye movement patterns, enhancing control accuracy over time. Furthermore, the integrated system continuously monitors the user's eye gaze and EEG signals in real time. It processes the data, recognizes the user's intentions, and generates appropriate control commands to drive the wheelchair accordingly. The wheelchair can be controlled by the user's gaze direction and motor intentions without the need for physical interaction. The eye gaze approach combined with EEG for wheelchair control offers a promising solution for individuals with disabilities, enabling them to operate the wheelchair using their eye movements and brain signals [21].

F. *EEG Only Wheelchair Control*

Using computer-brain or human-computer interaction methods to develop a neurophysiological protocol and brain-actuated switch for wheelchair control using EEG involves integrating neuroscience, computer science, and human-computer interaction principles [22]. Before anything, a neurophysiological protocol is developed to establish the relationship between specific brain activity patterns and intended wheelchair commands. This involves conducting experiments and collecting EEG data while participants perform motor imagery tasks related to wheelchair movements. The collected data is then analyzed to identify relevant brain signals or patterns that correlate with different commands. Signal processing techniques are then applied to preprocess the EEG data and extract relevant features to the identified brain signals. Machine learning algorithms are then trained on the extracted EEG features and corresponding wheelchair commands to build a classification model. This model learns to recognize patterns in the EEG data and classify them into different wheelchair control commands. Furthermore, the brain interface is designed to facilitate the interaction between the user and the wheelchair control system including visual feedback, virtual environments, or auditory cues to provide feedback and aid in the user's control and navigation. The developed neurophysiological protocol and brain-actuated switch are then evaluated through user studies and usability testing [23]. Feedback from participants is gathered to identify areas for improvement and refine the system iteratively. Once the system is developed and validated, it can be integrated with the wheelchair hardware and control system. The real-time EEG signals are processed using the trained classification model to generate control commands for the wheelchair. The wheelchair responds accordingly to the user's intended commands derived from their brain activity. Overall, developing a neurophysiological protocol and brain-actuated switch for wheelchair control using EEG is a complex and interdisciplinary task. It requires expertise in neuroscience, signal processing, machine learning, human-computer interaction, and wheelchair engineering [23].

G. *Stroke Rehabilitation*

The plasticity of the central nervous system refers to its ability to reorganize and form new connections in response to changes in inputs or experiences. In the context of stroke rehabilitation, repetitive rehabilitation training based on brain signals can harness the plasticity of the central nervous system to promote recovery and functional improvement in stroke patients [11]**.** To add some background information, a stroke occurs when there is a disruption of blood supply to the brain, leading to brain damage. This damage often results in functional impairments, such as paralysis or loss of coordination. Through repetitive rehabilitation training, specific motor tasks and exercises are repeatedly performed to encourage the brain to rewire and establish new connections related to the dysfunctional limb. This training can include various techniques such as physical therapy, occupational therapy, and task-specific training tailored to the individual's needs. In recent years, brain signal-based approaches, such as BCIs or neurofeedback, have emerged as promising tools for stroke rehabilitation. These techniques involve recording and analyzing brain signals, typically using EEG, and providing real-time feedback to the patient. Through repetitive rehabilitation training and brain signal-based interventions, the brain can establish new connections with the dysfunctional limb and the central nervous system. This process involves recruiting alternative neural pathways, activating dormant connections, and promoting functional reorganization in the brain. Additionally, through the use of EEG-based rehabilitation, such training can focus on activating the motor cortex of the brain, which is responsible for motor planning and execution. By engaging in motor imagery tasks, the patient generates specific brain signals associated with motor intention. This helps stimulate the activation of the motor cortex and facilitates the establishment of new connections related to the dysfunctional limb [24]. Over time, these new connections can contribute to the restoration of motor function and recovery of the affected limb. Overall, it's important to note that stroke rehabilitation is a complex and multifaceted process that often involves a combination of approaches, including physical therapy, pharmacotherapy, and psychological support [11]. The plasticity of the central nervous system provides a foundation for rehabilitation efforts to stimulate recovery and functional gains.

IV. Comparison and Classification of EEG Methods

A. Limitations

EEG signals have shown promise in various applications within smart health. However, there have been certain limitations to consider. One is the low signal-to-noise ratio. Moreover, EEG provides limited spatial resolution compared to other neuroimaging techniques like fMRI or PET scans. It measures electrical activity from the surface of the scalp, which can make it challenging to precisely localize the source of neural activity within the brain. With this in mind, EEG signals may not provide comprehensive information about subcortical structures or deep brain regions. Additionally, EEG signals are complex and require expertise in signal processing and neurophysiology for accurate interpretation [25]. Analyzing EEG data involves challenges such as distinguishing between different brain states, identifying specific cognitive processes, and extracting meaningful features for analysis. Considering that EEG signals can vary significantly across individuals due to anatomical characteristics, it can be challenging to develop generalized models or algorithms that apply to a diverse population. Lastly, wearing EEG electrodes and equipment can be burdensome for users, potentially affecting user acceptance and compliance [26]. Improving the comfort, ease of use, and wearability of EEG devices is crucial for their successful integration into smart health applications. Despite these limitations, ongoing research and technological advancements aim to address these challenges and improve the reliability, accuracy, and practicality of using EEG signals in smart health applications.

B. Advantages

Despite its limitations, using EEG signals in smart health can offer several advantages. It is noninvasive and can be used in various settings, including hospitals, clinics, or even at home, enabling long-term monitoring and data collection [26]. Also, EEG signals provide real-time measurements of brain activity, allowing for immediate analysis and interpretation. This enables prompt detection of abnormalities or changes in brain function, making it valuable for monitoring patients with neurological conditions or assessing cognitive states [26]. One advantage could include how EEG equipment is generally more affordable compared to other neuroimaging techniques. This makes EEG a cost-effective option for large-scale studies, long-term monitoring, or resource-limited healthcare settings. Not to mention, EEG signals can be used in neurofeedback training, where individuals can learn to self-regulate their brain activity for therapeutic purposes [25]. Additionally, EEG-based BCIs enable direct communication between the brain and external devices, allowing individuals to control external systems using their brain signals. Lastly, EEG data can be combined with other health information, such as medical records or wearable sensor data, to provide a more comprehensive understanding of an individual's health status. This can contribute to personalized healthcare approaches and targeted interventions tailored to an individual's specific needs. By leveraging the advantages of EEG signals in smart health, healthcare professionals and researchers can gain valuable insights into brain function, monitor neurological conditions, facilitate neurorehabilitation, and improve overall patient care.

V. Unsolved Research Problems

While EEG signal-based assistive technologies have made significant advancements, several research opportunities remain to further enhance their capabilities.

Signal processing and noise reduction in EEG recording, for example, are crucial for accurate interpretation and reliable performance of assistive technologies. Research can focus on developing advanced signal processing techniques to reduce artifacts, noise interference, and improve the signal-to-noise ratio [27].

Moreover, when it comes to adaptability and individualization, EEG signals may vary across individuals due to anatomical and physiological differences. Exploring methods to adapt EEG-based systems to individual users, including personalized calibration, user-specific feature extraction, and new machine learning algorithms, can enhance system performance and user experience [28].

In addition, multimodal integration can be considered a main unsolved research opportunity. Examples would be integrating other methods such as eye-tracking, electromyography (EMG), or other brain imaging techniques like functional near-infrared spectroscopy (fNIRS), which can provide complementary information for improved system performance [29]. Investigating the integration of multiple modalities can enhance the robustness and reliability of assistive technologies [30].

Furthermore, performance and usability with EEG-based assistive technologies need to be validated and tested in real-world environments to assess their usability, practicality, and user acceptance. Research can focus on conducting long-term studies, user feedback, and iterative design processes to improve the integration of these technologies into everyday life.

By addressing these research opportunities, the field of EEG signal-based assistive technologies can advance further, leading to improved performance, usability, and integration into the lives of individuals with disabilities [29].

VI. Conclusion

In conclusion, EEG signal technology holds great promise in the field of assistive technologies, offering several advantages and disadvantages. The current state of EEG signal technology showcases its potential for improving the lives of individuals with disabilities. However, it is important to consider both the benefits and limitations of this technology in order to fully understand its scope and impact. EEG signal technology has significant advantages in terms of non-invasiveness, communication assistance, device control, rehabilitation, and diagnostic applications. While EEG signal technology has been helpful for people with disabilities, challenges and limitations related to signal interpretation, electrode placement, spatial resolution, standardization, and capturing deep brain activity need to be addressed to fully utilize and improve its potential in improving the lives of individuals with disabilities.

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References

[1] World Health Organization. "World Mental Health Report: Transforming Mental Health for All," Geneva, Switzerland, 2022, pp 37.

[2] J. Á. Ariza and J. M. Pearce, "Low-Cost Assistive Technologies for Disabled People Using Open-Source Hardware and Software: A Systematic Literature Review," *IEEE Access*, vol. 10, 2022, pp. 124894-124927.

[3] Christos P. Panteliadis. "Historical Overview of Electroencephalography: from Antiquity to the Beginning of the 21st Century." *Journal of Brain and Neurological Disorders,* 2021.

[4] M. A. Eid, N. Giakoumidis and A. El Saddik, "A Novel Eye-Gaze-Controlled Wheelchair System for Navigating Unknown Environments: Case Study with a Person With ALS," *IEEE Access*, vol. 4, 2016, pp. 558-573.

[5] A. K, S. J. Kuruvila, S. Pramode and N. Krupa, "Brain Computer Interface for Neurorehabilitation with Kinesthetic Feedback," *5th International Conference on Robotics and Automation Engineering (ICRAE)*, Singapore, Singapore, 2020, pp. 153-157.

[6] S. S. P. Kumar and L. Ajitha, "Early Detection of Epilepsy Using EEG Signals," *International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT)*, Kanyakumari, India, 2014, pp. 1509-1514.

[7] T. Sudhakar, G. Hari Krishnan, N. R. Krishnamoorthy, B. Janney J, M. Pradeepa and J. P. Raghavi, "Sleep Disorder Diagnosis using EEG based Deep Learning Techniques," *2021 Seventh International conference on Bio Signals, Images, and Instrumentation* (ICBSII), Chennai, India, 2021, pp. 1-4.

[8] Centers for Disease Control and Prevention. Disability and Health Data System (DHDS) [Internet]. [updated 2023 May; cited 2023 May 15].: http://dhds.cdc.gov

[9] C. -K. Huang, Z. -W. Wang, G. -W. Chen and C. -Y. Yang, "Development of a Smart Wheelchair With Dual Functions: Real-Time Control and Automated Guide," *2nd International Conference on Control and Robotics Engineering (ICCRE)*, Bangkok, Thailand, 2017, pp. 73-76.

[10] E. V. K. Rao, N. Y. Reddy, B. V. S. S. Greeshma, and Y. S. S. V. Reddy, "EEG Based Smart Wheelchair for Disabled Persons Using Non-Invasive BCI," *2022 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES)*, May 2022, p. 440-446.

[11] M. Butt, G. Naghdy, F. Naghdy, G. Murray and H. Du, "Assessment of Neuroplasticity Using EEG Signal in Rehabilitation of Brain Stem Stroke Patients," IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), London, ON, Canada, 2020, pp. 1-4.

[12] S. Cheng, J. Wang, L. Zhang and Q. Wei, "Motion Imagery-BCI Based on EEG and Eye Movement Data Fusion," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 12, December 2020, pp. 2783-2793.

[13] K. Haltas, A. Erguzen and E. Erdal, "Classification Methods in EEG Based Motor Imagery BCI Systems," *3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, Ankara, Turkey, 2019, pp. 1-5.

[14] S. Lee, Y. Shin, S. Woo, K. Kim and H. -N. Lee, "Dry Electrode Design and Performance Evaluation for EEG Based BCI Systems," *International Winter Workshop on Brain-Computer Interface (BCI)*, Gangwon, Korea (South), 2013, pp. 52-53.

[15] J. Rouillard *et al.*, "Hybrid BCI Coupling EEG and EMG for Severe Motor Disabilities," *Procedia Manufacturing,* vol. 3, 2015, pp. 29-36.

[16] Z. Lasefr, S. S. V. N. R. Ayyalasomayajula and K. Elleithy, "Epilepsy Seizure Detection Using EEG Signals," *IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)*, 2017, pp. 162-167.

[17] M. Aljshamee, R. Alsabah, A. H. Mousa and A. Alsabbagh, "(Portable) Low-Cost Electroencephalogram (EEG) Recorder for Brain Computer-Interface (BCI)," *11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, Kharagpur, India, 2020, pp. 1-6.

[18] S. Jamal, M. V. Cruz, S. Chakravarthy, C. Wahl, and H. Wimmer, "Integration of EEG and Eye Tracking Technology: A Systematic Review," *SoutheastCon 2023*, April 2023, pp. 209-216.

[19] N. Wanluk, S. Visitsattapongse, A. Juhong, and C. Pintavirooj, "Smart Wheelchair Based on Eye Tracking," *9th Biomedical Engineering International Conference (BMEiCON)*, December 2016, pp.1-4.

[20] E. Albilali, H. Aboalsamh, and A. Al-Wabil, "Comparing Brain-Computer Interaction and Eye Tracking as Input Modalities: An Exploratory Study," *International Conference on Current Trends in Information Technology (CTIT)*, December 2013, pp. 232-236.

[21] D. W. K. Ng, Y. W. Soh, and S. Y. Goh, "Development of an Autonomous BCI Wheelchair," *IEEE Symposium on Computational Intelligence in Brain Computer Interfaces (CIBCI)*, December 2014, pp. 1-4.

[22] L. Cao, J. Li, H. Ji, and C. Jiang, "A Hybrid Brain Computer Interface System Based on the Neurophysiological Protocol and Brain-Actuated Switch for Wheelchair Control," Journal of Neuroscience Methods, vol. 229, May 2014, pp. 33-43.

[23] R. N. Khushaba, C. Wise, S. Kodagoda, J. Louviere, B. E. Kahn, and C. Townsend, "Consumer Neuroscience: Assessing the Brain Response to Marketing Stimuli Using Electroencephalogram (EEG) and Eye Tracking," *Expert Systems with Applications,* vol. 40, 2013.

[24] F. Cincotti et al., "EEG-Based Brain-Computer Interface to Support Post-Stroke Motor Rehabilitation of the Upper Limb," *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, San Diego, CA, USA, 2012, pp. 4112- 4115.

[25] M. Z. Ilyas, P. Saad and M. I. Ahmad, "A Survey of Analysis and Classification of EEG Signals for Brain-Computer Interfaces," *2nd International Conference on Biomedical Engineering (ICoBE)*, Penang, Malaysia, 2015, pp. 1-6.

[26] R. -J. Chang, C. -R. Wu, K. -Y. He and B. -S. Lin, "A Flexible and Wearable EEG Device," *Third International Conference on Computing Measurement Control and Sensor Network (CMCSN)*, Matsue, Japan, 2016, pp. 48-51.

[27] M. Thulasidas, Cuntai Guan and Jiankang Wu, "Robust Classification of EEG Signal for Brain-Computer Interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, no. 1, March 2006, pp. 24-29.

[28] T. Ren, Y. Xu, C. Gu, F. Chen and G. Wei, "Studies on Calibration of Electroencephalographic Biofeedback Equipment," *3rd International Academic Exchange Conference on Science and Technology Innovation (IAECST)*, Guangzhou, China, 2021, pp. 1511-1514.

[29] A. Saboor et al., "Mesh of SSVEP-Based BCI and Eye-Tracker for Use of Higher Frequency Stimuli and Lower Number of EEG Channels," *International Conference on Frontiers of Information Technology (FIT)*, December 2018, pp. 99-104.

[30] P. L. Purdon, C. Lamus, M. S. Hämäläinen and E. N. Brown, "A State Space Approach to Multimodal Integration of Simultaneously Recorded EEG and fMRI," *IEEE International Conference on Acoustics, Speech and Signal Processing*, 2010, pp. 5454-5457.

[31] "Electroencephalography," *Encyclopædia Britannica*. May 14, 2024. Accessed: Jun. 03, 2024. [Online]. Available: https://www.britannica.com/science/electroencephalography