DOI https://doi.org/10.24297/ijct.v23i.9485

Design and Implementation of P300 Brain-Controlled Wheelchair with a Developed Wireless DA Converter

Zizhu Li[1], Boning Li[1], Wenping Luo[2], and Jianting Cao[1,3]

[1]Graduate School of Engineering, Saitama Institute of Technology, Fukaya 369-0217, Japan
[2]School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China
[3]RIKEN Center for Advanced Intelligence Project(AIP), 103-0027, Japan

Email addresses {i3003lqa, i1005sui}@sit.ac.jp; adleyluo@163.com;
Correspondence: cao@sit.ac.jp

Abstract

This article presents a P300 brain-controlled wheelchair system utilizing a wireless Digital-to-Analog converter for signal transmission. The wireless Digital-to-Analog converter addresses issues with device connectivity and simplifies signal transmission, removing the need for complex serial port protocols. A support vector machine model is trained to extract the P300 component from the Electroencephalogram signal. A P300 stimulator is designed to elicit the P300 component response, with subjects controlling the wheelchair's movement by looking at randomly flickering white circles. Experimental validation is conducted on a modified wheelchair, demonstrating the effectiveness and reliability of the proposed method.

Keywords: wireless Digital-to-Analog converter, Brain-Controlled System, P300, Support vector machine

Introduction

In recent years, there has been significant progress in human-machine interaction technology, particularly in brain-computer interface (BCI) technology Korovesis et al., 2019; LUO et al., 2021; Mahmoud et al., 2018. BCI technology involves analyzing brain neural signals and converting them into control signals to enable control of external devices, which has promising applications in various fields. One notable application is the brain-controlled wheelchair system, which enhances mobility and improves the quality of life for individuals with disabilities Bickenbach et al., 1999. Experiments with many methods to drive wheelchairs for dis- abled people have been used in many BCI systematic studies, which gives us some references Cao et al., 2014; Carrasquilla-Batista et al., 2017; Choi and Cichocki, 2008; Li et al., 2013; Pires et al., 2008; Stamps and Hamam, 2010; Tang et al., 2018; Voznenko et al., 2018; Wang and Yu, 2017; Zhang et al., 2015. However, there are still challenges in this field, such as the limited cable length and transmission speed of the DA converter connecting the brainwave detector and the controlled wheelchair, and the large size of the system, which makes it inconvenient to carry outdoors. To address these issues, wireless transmission has emerged as a viable solution.

In wireless DA converters, data transmission is typically carried out using wireless signals, which makes the signal transmission speed subject to the influence of wireless channels, including interference and attenuation. Higher signal frequencies and broader bandwidths are often required to achieve high-speed data transmission. This may lead to some signal distortion, which can affect accuracy. Therefore, in wireless DA converters, there is usually a trade-off between speed and accuracy. However, depending on the requirements of the usage environment, the use of wireless DA converters by wheelchair users undoubtedly offers greater freedom. In addition, the P300 electroencephalogram(EEG) signal has been widely used in BCI technology, and using it as a control signal can improve system accuracy and reliability Huang et al., 2019; Kaufmann et al., 2014; Van de Plassche, 2013; Yu et al., 2017.In order to address the lack of availability in the market and provide convenience to users, we have developed a P300 brain-controlled wheelchair system with a wireless DA converter.

In this paper, a P300 Brain-Controlled Wheelchair with a Wireless DA Converter is presented. Unlike conventional DA converters, the wireless DA converter is a new controller that enhances the system's reliability and convenience. The device transmits digital signals wirelessly to the microcontroller, which converts them into assembly language commands and encodes them into analog signal instructions Luschas et al., 2004. Finally, the analog signal instructions control the wheelchair via a signal amplifier. The wireless DA converter addresses the connection issues between the brainwave detector and the device, eliminates complex serial port protocols, and simplifies the transmission of control signals. The study uses a Support vector machine(SVM)model to extract P300 waveform features from the EEG signal, which has a strong generalization ability in high-dimensional space, can handle high-dimensional feature data better, and has low overfitting risk Suthaharan, 2015. The P300 stimulator was designed to detect the P300 waveform features when the subject looked at randomly flickering white circles. The stimulator can be adjusted based on the user's needs.

Our study mounted a Wireless DA Converter onto a P300 Brain-Controlled Wheelchair system for experimental validation. The study findings suggest that the implementation of a DA converter for signal transmission in a P300 brain-controlled wheelchair system is efficacious, thereby providing a foundation for further inquiry in this domain. Given the ongoing advancements in BCI technology and wireless communication,brain-controlled wheelchair systems hold great potential for future applications.

BCI Control System of Wheelchairs

In this study, a Brain-controlled wheelchair system was applied to control the movement of an electric wheelchair (Fig. 1), which consisted of a wireless DA converter, an EEG acquisition device, and a P300 speller stimulator device. The wireless DA converter communicated with the powered wheelchair through wireless means, and the direction of movement was determined based on the user's gaze and P300 responses. The subject interacted with the computer and transmitted information through the P300 stimulator to the computer. Subsequently, the computer issued commands to the wheelchair drive unit to control movement. The hardware of the wheelchair was enhanced, and a drive unit was designed to enable control of the wheelchair's movement via a P300 stimulator. The modification included retaining the rocker control unit of the wheelchair to allow for manual operation when necessary.

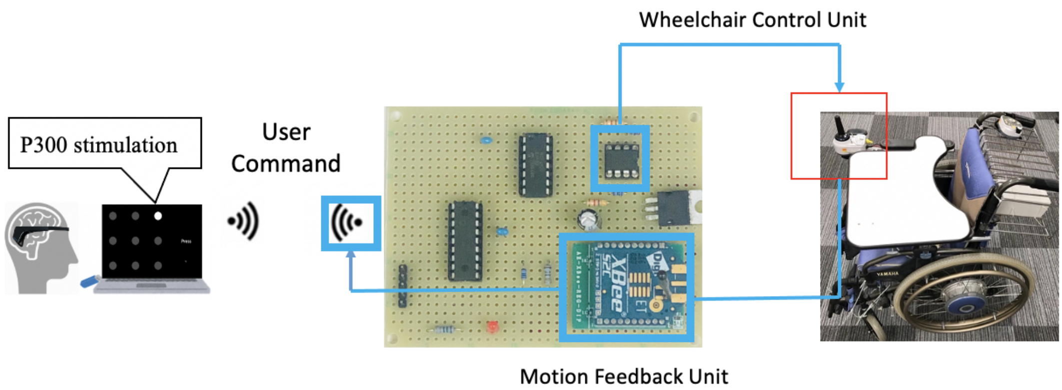

Fig. 1. Schematic diagram of the BCI system for Wireless DA Converter.

P300 paradigm and P300 stimulator. Stimulus paradigms commonly employed in Brain-Computer Interface (BCI) research comprise motor imagery (MI), steady-state visually evoked potential (SSVEP), and P300.MI involves imagining movements without actual muscle activity and is suitable for controlling prosthetics and wheelchairs, but has higher noise levels and weaker amplitudes compared to actual muscle movements. SSVEP signals only require visual stimulation but are limited by frequency range and may be affected by noise or visual impairments.

P300 signals have high signal quality and accuracy, do not require specific tasks or movements, and offer greater flexibility and user freedom, making them ideal for individuals with physical disabilities or mobility impairments. P300 can be used for a variety of control tasks, resulting in better BCI performance and control accuracy than MI and SSVEP. The P300 paradigm can also adapt during use, automatically adjusting stimulus parameters and algorithms to improve performance and user experience. MI and SSVEP have limited universality and user freedom. We chose the P300 paradigm as our BCI model due to its advantages over MI and SSVEP.

To elicit P300 potentials, a stimulator designed to evoke visual stimuli was developed, referred to as the P300 stimulator. The P300 stimulator utilized the "pygame" module in Python to generate a 3 x 3 grid consisting of nine regions, which were divided into blocks numbered 1 to 9 (Fig. 2). The stimulator presented four images: a gray circle (non-target stimulus), a white circle (target stimulus), a background image (9-box grid), and a press screen (for recording click times). During the execution of the stimulator, the white and gray circles were proportionally reduced in size against the background of the 9-box grid. The white circle image appeared at a randomly selected position within the grid, followed by a second white circle image, which appeared after 800 ms and covered a different position within the 9-box grid.

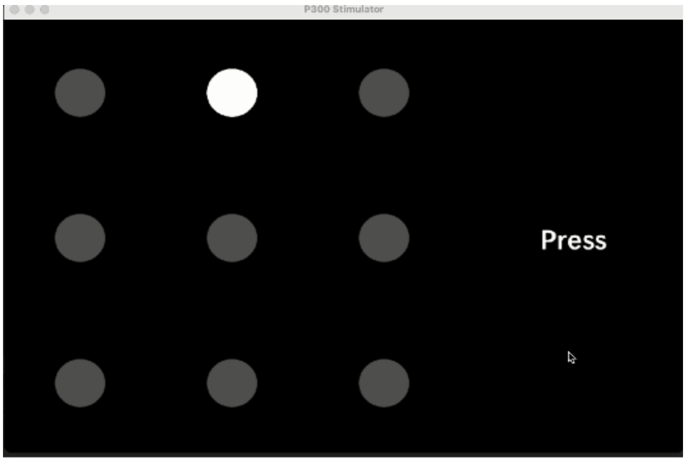

Fig. 2. Diagram of the P300 Stimulator.

designed a custom P300 stimulator that can offer tailored benefits to meet the research objectives of P300-based wheelchair control. Parameters such as stimulation mode, frequency, duration, and intensity can be fine-tuned accordingly. Moreover, a designed P300 stimulator may potentially provide enhanced stimulation efficacy and signal-to-noise ratio. By combining advanced hardware or software algorithms, the stimulator can be optimized to improve its performance and reliability, resulting in more accurate and robust P300 signals.

A Comprehensive Overview of the Offline and Online Workflow of P300 paradigms. P300 paradigms are typically divided into offline and online phases because this type of BCI model requires both training and testing phases. During the offline training phase, a large amount of data is collected from subjects and analyzed to develop the model and algorithms. Finally, the model was trained as a classifier. This phase can be conducted offline without being integrated into real-world tasks or applications. The online phase requires real-time data processing and control to implement real-time control of machines or devices and verify the performance and practicality of the P300 model. Thus, separating P300 into offline and online phases can better distinguish the requirements of different stages and achieve better training, testing, and application of P300 models.

The BCI system is comprised of two phases (Fig. 3): an offline phase, where the classifier is trained on previously collected data, and an online phase, where the classifier is used to decode real-time EEG signals. MUSE was used to capture EEG in this trial.

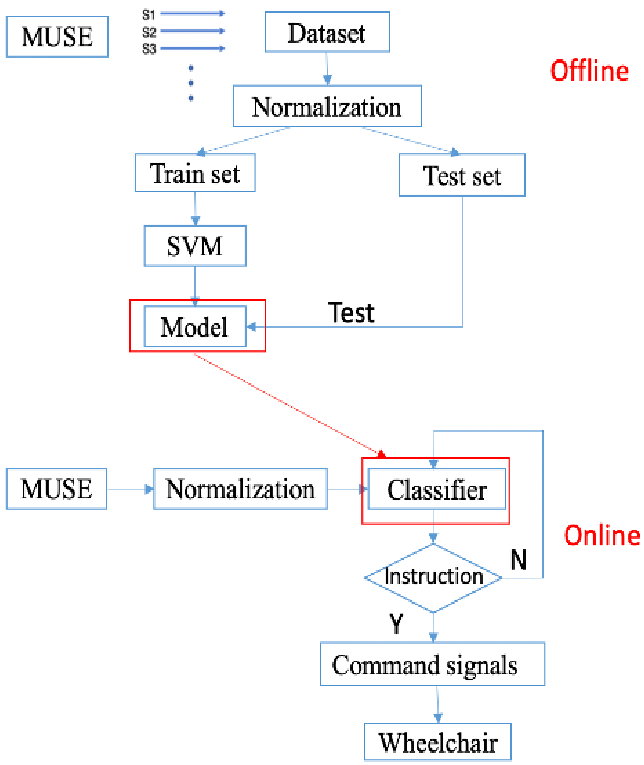

Fig. 3. Workflow of the P300 Paradigms.

Support Vector Machine. linear discriminant analysis(LDA) and SVM are common classifiers used in P300 experiments. LDA is a fast and efficient linear classifier that extracts important information from multiple feature dimensions and reduces redundant information. However, LDA assumes normal data distributions and is sensitive to noise and outliers, making it less suitable for non-linear classification problems.

SVM is better suited for high-dimensional data processing due to its ability to map data from low to high-dimensional space using kernel functions. It can handle non-linear classification problems, making it essential in P300 signal recognition. However, SVM requires parameter adjustment and long computation time, making it less suitable for online processing. After comparison, we believe that SVM has more advantages in extracting P300 feature signals.

It differs from ordinary pattern recognition models in that it performs margin maximization and kernel tricks. Margin maximization is the shortest distance between the boundary and the data. Figure 4 shows the image of marginal maximization, the idea of margin maximization is to draw the boundary as far away as possible from the data that is closest to the boundary between the two classes. The purple data points represent the target data, while the green data points represent the non-target data.

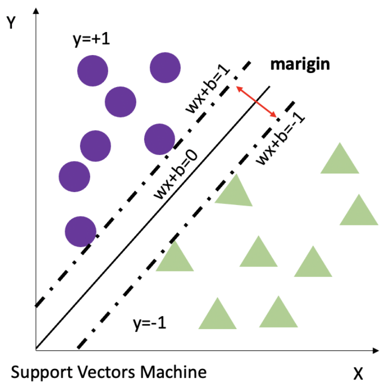

Fig. 4. Schematic diagram of margin maximization.

The values y=+1 and y=-1 are used to represent the class labels of the samples. The equation wx+b=0 represents the hyperplane that separates the two classes of data points, where w is the normal vector of the hyperplane and b is the intercept. The equations wx+b=1 and wx+b=-1 represent two parallel hyperplanes that are at a distance of 1 from the hyperplane wx+b=0. These equations are used to determine the boundary region, i.e., the decision boundary of the classifier. During the classification process, data points are mapped onto either side of the hyperplane and are allocated to the corresponding class.

When facing nonlinearly separable data, it becomes necessary to utilize kernel tricks in SVM to map the data from its original space to a new feature space. This is illustrated in Fig. 5, where a 2-dimensional feature space is mapped to a 3-dimensional feature space. The training data is then used in the new feature space to obtain the learning model using linear methods.

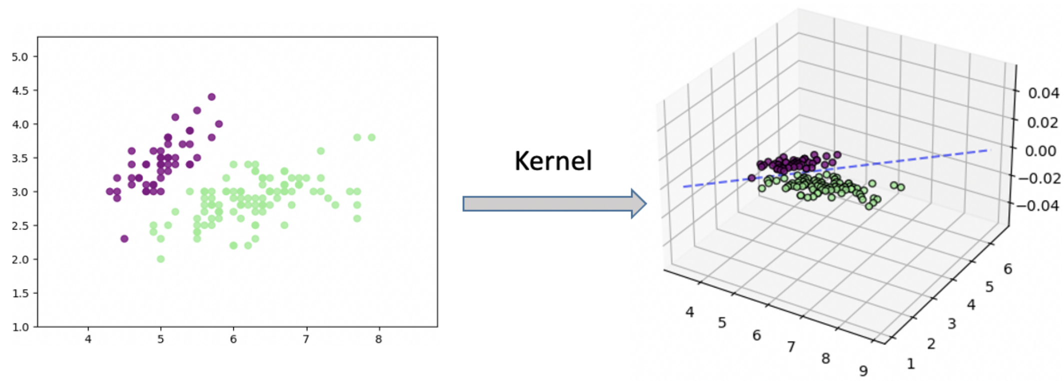

Fig. 5. The 2D feature space is mapped to the 3D feature space.

To find a map of the feature space, we need to find the inner product $\phi(x)^T\phi(y)$ on the feature space. The kernel trick allows us to calculate the inner product on the feature space without knowing what the feature space is and what ϕ is. The discriminant function, denoted as $f(x)$, is defined as follows:

$$f(x) = \text{sign}\left[\sum_{i=1}^{n} a_i y_i \phi(x_i)^T \phi(x)\right] \tag{1}$$

Here, a_i represents the weight associated with the i-th learning data x_i, y_i represents the label (either 1 or -1) associated with x_i, and x represents the input data for which we want to predict the label. The function sign[ ] returns +1 if the argument is positive, and -1 otherwise.

The kernel function, denoted as $k(x, y)$, is defined as follows:

$$k(x, y) = \phi(x)^T \phi(y) \tag{2}$$

It represents the inner product between the mapped feature vectors $\phi(x)$ and $\phi(y)$ in the feature space.

By substituting the inner product of the discriminant function with the kernel function, we obtain a modified form of the discriminant function:

$$f(x) = \text{sign}\left[\sum_{i=1}^{n} a_i y_i k(x_i, x)\right] \tag{3}$$

In this modified form, the inner product between the feature vectors $\phi(x_i)$ and $\phi(x)$ is replaced by the kernel function $k(x_i, x)$. This allows us to compute the discriminant function without explicitly calculating the feature vectors in the feature space, but rather by working with the kernel function directly.

After SVM extracts the characteristic P300 signal, it can be transformed into digital signals to send commands through the wireless module. The digital signals are then converted into analog signals, specifically voltage, using a DA converter to control the wheelchair.

Development of a Wireless DA Converter for P300 Brain-Controlled Wheelchair

Design and Implementation of a Wireless DA Converter. We have developed a nested wireless DA converter, specifically designed for wheelchair control using a BCI system. This converter combines wireless signal transmission and digital signal processing technologies, resulting in enhanced flexibility and adaptability to diverse application scenarios and usage requirements. The simplified installation process, attributed to the absence of complex wired connections, saves both time and labor costs. Moreover, wireless signal transmission technology enables greater transmission distances, providing flexibility and convenience compared to wired connections. Additionally, the device's compact size facilitates easier integration into wheelchairs and other equipment. The drive circuit board schematic, shown in Fig. 6, was designed to improve the portability of the interactive system by eliminating the need for complicated communication protocols with controlled devices. The DA Converter integrates a wireless communication serial port, allowing for wireless communication between the computer and the wheelchair. Wireless DA Converter describes a wheelchair control system consisting of five modules, namely a wireless communication module (Xbee-S2B), a microcontroller (Microchip's PIC16F88 series and MCP4922 chip), a differential amplifier (LM358), and a driver module for the converter (TA7805). The system employs the output voltages of the differential amplifier (VA and VB) to control the movement of the wheelchair. Specifically, when both output voltages reach a pre-defined stop voltage, the wheelchair comes to a halt; when VA outputs the set voltage, the wheelchair moves forward or backward; and when VB outputs the set voltage, the wheelchair moves left or right.

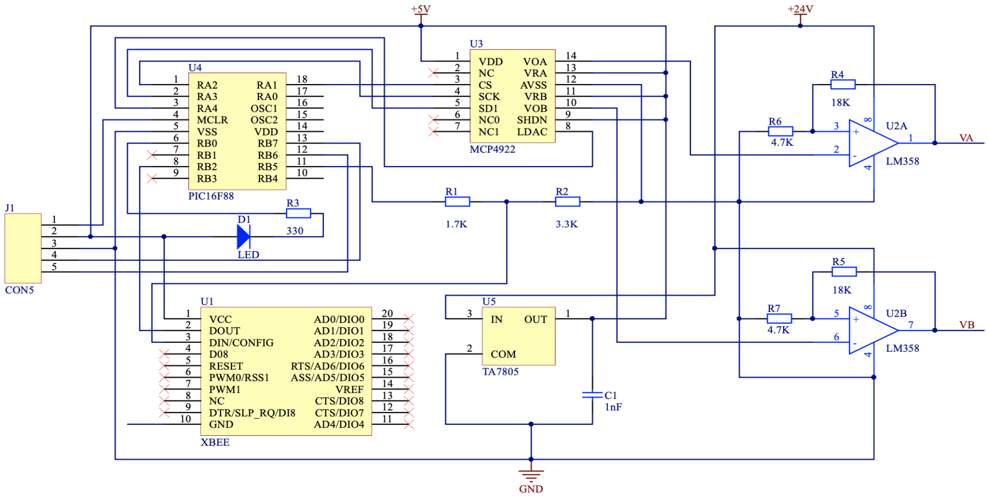

Fig. 6. Circuit schematic of the Wireless DA Converter.

The MCP4922 is a dual 12-bit DAC chip with an SPI interface, built-in voltage reference circuit, and low power consumption, suitable for industrial control and medical devices. The PIC16F88 is a low-power, high-performance microcontroller with rich peripherals and interrupt modes, making it ideal for prototyping designs. The LM358 is a low-power, dual-operational amplifier with high accuracy and stability, while the TA7805 is a 5V fixed positive voltage regulator that provides stable output for DC power supplies with a high output current. These components are interconnected to form a complete wireless DA converter. The Xbee-S2B is a ZigBee-based wireless communication module that supports various network topologies and data transmission modes while providing high security and reliability. Figure 7 shows the wireless DA converter after completion.

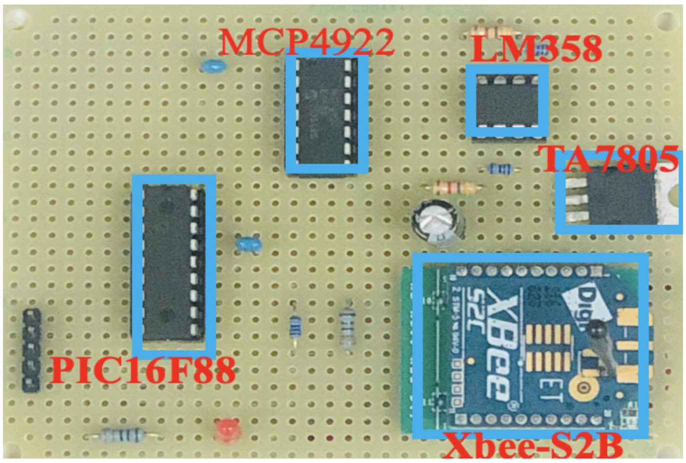

Fig. 7. Physical circuit diagram of the wireless DA converter.

Digital-to-Analog converter chips MCP4922. To drive the wheelchair using analog signals, it is necessary to convert the discrete digital signals, which are generated by sending commands from a computer, into continuous analog signals. Therefore, the design of a wireless digital-to-analog converter (DAC) with DAC chips as the converter components is proposed. During the design of our wireless DA converter circuit, we will adopt this converter. This design enables the conversion of digital signals into analog signals with continuous values for the purpose of driving the wheelchair.

Design Principles of DAC. The principle of a DAC involves a resistor array and n number of current switches. The switches are toggled based on the digital input value, generating a current proportional to the input value. Due to the low switching error of current switches, they are commonly used in DAC circuits. If a voltage output is required, the generated current is converted to voltage using additional circuitry (Fig. 8).

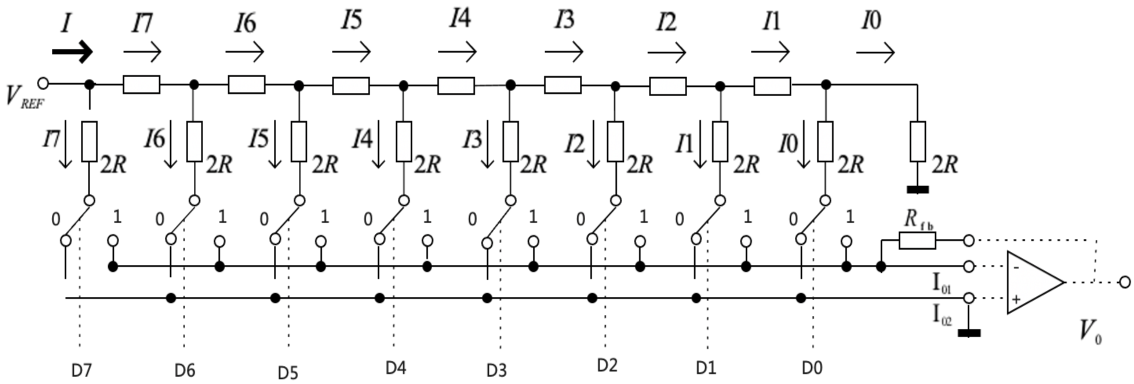

Fig. 8. Schematic Diagram of DAC.

$$I = \frac{V_{\mathrm{REF}}}{R} \tag{4}$$

$$I_7 = \tfrac{I}{2^1}, \ldots, I_0 = \tfrac{I}{2^8}$$

where I is the output current, V_REF is the reference voltage, and R is the resistance of the load.

$$I_{o1} = I_7 + \cdots + I_1 = \left(\frac{I}{2^8}\right) \times (2^7 + \cdots + 2^0) \tag{5}$$

$$I_{o2} = 0$$

When the input data D7 to D0 is 1111 1111B, it means that the binary value is 255, which means that the value in decimal is 255.

$$\begin{aligned} R_{fb} &= R \\ V_O &= -I_{o1} \times R_{fb} \\ &= -I_{o1} \times R \\ &= -\left(\frac{V_{\mathrm{REF}}/R}{2^8}\right) \times (2^7 + \cdots + 2^0) \times R \\ &= -\tfrac{V_{\mathrm{REF}}}{2^8} \times (2^7 + \cdots + 2^0) \end{aligned} \tag{6}$$

If $R_{fb} = R$, it can be seen from Formula 3 that the magnitude of the output voltage is directly proportional to the digital quantity. The required digital quantity can be calculated accordingly (Table 1).

Table 1. Bit numbers for 5 types of instructions.

Command/ Data bit	VA	VB
Forward	1024	592
Back	256	592
left	592	1042
right	592	256
stop	592	592

Resolution. Resolution is defined as the smallest increment of change in the output analog voltage that can be detected corresponding to a change in the least significant bit (LSB) of the input digital quantity. It represents the minimum discernible change in the output analog quantity.

$$U_{\mathrm{LSB}}/U_m = 1/(2^n - 1) \tag{7}$$

Resolution is determined in relation to the number of bits of the input digital quantity, Um is the full-scale voltage, n is the number of binary bits for a full scale of 5V, and the resolution is 5V/4095 = 1.22mV when using a 12-bit DAC.

By considering the minimum detectable change of the output analog quantity and conducting careful calculations, we have determined that the voltage output of the wheelchair can be effectively controlled. This control is achieved by amplifying the output analog quantity by a factor of 2.92 using double operational amplifiers. The details of the voltage output control are presented in Table 2.

Table 2.Control of the wheelchair's voltage output.

Command / Output Voltage	VA	VB
Forward	3.58	2.63
Back	1	2.63
left	2.63	3.64
right	2.63	1
stop	2.63	2.63

Experimental Results and Discussions

Experimental Setup and Conditions. In the preparation phase, offline training of the P300 paradigm was conducted. In this experiment, EEG data was collected using the Muse headband from the participants, and a large dataset was gathered for training an SVM model. Subsequently, the online testing phase was initiated. A P300 stimulator, developed by our team, was used to provide stimulation, while real-time detection of the P300 signal in the EEG was performed using the Muse headband. Upon detecting a P300 signal, the detected signal was converted into a command and transmitted wirelessly to control the wheelchair using our designed wireless DA converter.

Results of Real-time experiment. A group of five participants underwent a single experimental session in which they controlled the movement of a wheelchair using a P300 Brain-Controlled System (Fig. 9). The participants were instructed to use five basic commands, namely forward, backward, left, right, and stop, to navigate the wheelchair. The experimental protocol involved the following sequence of wheelchair movements: forward motion, pause, backward motion, pause upon returning to the starting position, left rotation, pause, right rotation returning to the starting position, and final pause. All five participants successfully completed the experiment and demonstrated smooth control of their wheelchairs. The minimum completion time for all participants was 2 minutes, while the maximum was 3 minutes.

Fig. 9.One of the subjects driving the wheelchair.

Discussion of results. The experimental results show that Wireless DA Converter could effectively control the wheelchair to complete the related movements. However, the test subjects had to concentrate on controlling the wheelchair movement throughout the experiment, which was a problem. As a future research topic, the controlled device can provide some feedback to the human body so that it can be alerted in time when the operator is not focused enough.

Conclusions

This paper explores the feasibility of implementing a wireless digital-to-analog (DA) converter in a brain-computer interface (BCI) system for controlling a motorized wheelchair. The study involved modifying the hardware of the wheelchair to develop a hardware drive system that allows it to receive commands wirelessly from the user's EEG signals via the P300 BCI. To validate the results, the P300 BCI system was ported to a powered wheelchair, where an SVM-trained model was used to extract P300 waveform features from the EEG signal. A P300 stimulator was also designed to detect P300 waveform features when the user looked at randomly flashing white circles. The system achieved an accuracy rate of 89%, which indicates the potential for further improvement. The study demonstrates the effectiveness of using a wireless DA converter for signal transmission in a P300 BCI system for controlling a motorized wheelchair. The results could be used to develop more advanced brain-controlled systems, such as brain-controlled toys and drones, that utilize wireless DA converters.

Acknowledgments

This work was supported by JSPS KAKENHI 20H04249.

Conflicts of Interest

The authors have no conflict of interest about anything in this article.

References

Bickenbach, J. E., Chatterji, S., Badley, E. M., & Üstün, T. B. (1999). Models of disablement, universalism and the international classification of impairments, disabilities and handicaps. *Social science & medicine*, *48*(9), 1173–1187. https://doi.org/https://doi.org/10.1016/S0277-9536(98)00441-9

Cao, L., Li, J., Ji, H., & Jiang, C. (2014). A hybrid brain computer interface system based on the neurophysiological protocol and brain-actuated switch for wheelchair control. *Journal of neuroscience methods*, *229*, 33–43. https://doi.org/https://doi.org/10.1016/j.jneumeth.2014.03.011

Carrasquilla-Batista, A., Quirós-Espinoza, K., & Gómez-Carrasquilla, C. (2017). An internet of things (iot) application to control a wheelchair through eeg signal processing. *2017 International Symposium on Wearable Robotics and Rehabilitation (WeRob)*, 1–1. https://doi.org/https://doi.org/10.1109/WEROB.2017.8383877

Choi, K., & Cichocki, A. (2008). Control of a wheelchair by motor imagery in real time. *Intelligent Data Engineering and Automated Learning–IDEAL 2008: 9th International Conference Daejeon, South Korea, November 2-5, 2008 Proceedings 9*, 330–337. https://doi.org/https://doi.org/10.1007/978-3-540-88906-9_42

Huang, Q., Zhang, Z., Yu, T., He, S., & Li, Y. (2019). An eeg-/eog-based hybrid brain-computer interface: Application on controlling an integrated wheelchair robotic arm system. *Frontiers in neuroscience*, *13*, 1243. https://doi.org/https://doi.org/10.3389/fnins.2019.01243

Kaufmann, T., Herweg, A., & Kübler, A. (2014). Toward brain-computer interface based wheelchair control utilizing tactually-evoked event-related potentials. *Journal of neuroengineering and rehabilitation*, *11*, 1–17. https://doi.org/https://doi.org/10.1186/1743-0003-11-7

Korovesis, N., Kandris, D., Koulouras, G., & Alexandridis, A. (2019). Robot motion control via an eeg-based brain–computer interface by using neural networks and alpha brainwaves. *Electronics*, *8*(12), 1387. https://doi.org/https://doi.org/10.3390/electronics8121387

Li, Y., Pan, J., Wang, F., & Yu, Z. (2013). A hybrid bci system combining p300 and ssvep and its application to wheelchair control. *IEEE Transactions on Biomedical Engineering*, *60*(11), 3156–3166. https://doi.org/https://doi.org/10.1109/TBME.2013.2270283

LUO, W., CAO, J., ISHIKAWA, K., & JU, D. (2021). Experimental validation of intelligent recognition of eye movements in the application of autonomous vehicle driving. *International Journal of Biomedical Soft Computing and Human Sciences: the official journal of the Biomedical Fuzzy Systems Association*, *26*(2), 63–72. https://doi.org/https://doi.org/10.24466/ijbschs.26.2_63

Luschas, S., Schreier, R., & Lee, H.-S. (2004). Radio frequency digital-to-analog converter. *IEEE Journal of Solid-State Circuits*, *39*(9), 1462–1467. https://doi.org/https://doi.org/10.1109/JSSC.2004.829377

Mahmoud, A., Hamoud, M., Ahmad, A. M., & Ahmad, A. S. (2018). Controlling a wheelchair using human-computer interaction. *Int. J. Sci. Res*, *7*, 681–686. https://doi.org/https://doi.org/10.21275/5011802

Pires, G., Castelo-Branco, M., & Nunes, U. (2008). Visual p300-based bci to steer a wheelchair: A bayesian approach. *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 658–661. https://doi.org/https://doi.org/10.1109/IEMBS.2008.4649238

Stamps, K., & Hamam, Y. (2010). Towards inexpensive bci control for wheelchair navigation in the enabled environment–a hardware survey. *Brain Informatics: International Conference, BI 2010, Toronto, ON, Canada, August 28-30, 2010. Proceedings*, 336–345. https://doi.org/https://doi.org/10.1007/978-3-642-15314-3_32

Suthaharan, S. (2015). *Machine learning models and algorithms for big data classification: Thinking with examples for effective learning* (Vol. 36). Springer. https://doi.org/https://doi.org/10.1007/978-1-4899-7641-3

Tang, J., Liu, Y., Hu, D., & Zhou, Z. (2018). Towards bci-actuated smart wheelchair system. *Biomedical engineering online*, *17*(1), 1–22. https://doi.org/https://doi.org/10.1186/s12938-018-0545-x

Van de Plassche, R. J. (2013). *Cmos integrated analog-to-digital and digital-to-analog converters* (Vol. 742). Springer Science & Business Media. https://doi.org/https://doi.org/10.1007/978-1-4757-3768-4

Voznenko, T. I., Chepin, E. V., & Urvanov, G. A. (2018). The control system based on extended bci for a robotic wheelchair. *Procedia computer science*, *123*, 522–527. https://doi.org/https://doi.org/10.1016/j.procs.2018.01.079

Wang, D., & Yu, H. (2017). Development of the control system of a voice-operated wheelchair with multi-posture characteristics. *2017 2nd Asia-Pacific Conference on Intelligent Robot Systems (ACIRS)*, 151–155. https://doi.org/https://doi.org/10.1109/ACIRS.2017.7986083

Yu, Y., Zhou, Z., Liu, Y., Jiang, J., Yin, E., Zhang, N., Wang, Z., Liu, Y., Wu, X., & Hu, D. (2017). Self-paced operation of a wheelchair based on a hybrid brain-computer interface combining motor imagery and p300 potential. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *25*(12), 2516–2526. https://doi.org/https://doi.org/10.1109/TNSRE.2017.2766365

Zhang, R., Li, Y., Yan, Y., Zhang, H., Wu, S., Yu, T., & Gu, Z. (2015). Control of a wheelchair in an indoor environment based on a brain–computer interface and automated navigation. *IEEE transactions on neural systems and rehabilitation engineering*, *24*(1), 128–139. https://doi.org/https://doi.org/10.1109/TNSRE.2015.2439298