EEG Brainwave Controlled Robotic Arm for Neurorehabilitation Training

ChenWenyi[1*], *WangRuike*[2], *YanBohan*[3], *LiYuxuan*[4]
1 School of Engineering, Shantou University, Shantou 515063 China
2 School of Biomedical Engineering, Northeastern University, Shenyang 110000, China
3 School of Biomedical Engineering, Northeastern University, Shenyang 110000, China
4 School of Biomedical Engineering, Northeastern University, Shenyang 110000, China
*Correspondence: 22wychen@stu.edu.cn

1. Abstract

This study presents an EEG-based control method using AI for a robotic arm neurorehabilitation system. The system employs advanced EEG technology to capture and interpret brainwaves, utilizing AI algorithms for analysis and translation. This enables users to control the robotic arm via neural signals during neurorehabilitation training. Real-time feedback and adaptive AI ensure a personalized, interactive experience, and adjust the program based on user progress. This approach aims to enhance neurorehabilitation outcomes by promoting neuroplasticity and motor skill recovery in individuals with neurological disorders or injuries. The study's results highlight AI's positive impact on the system, suggesting EEG-based AI control could play a pivotal role in neurorehabilitation.

2. Study Results

2.1. Methodology

2.1.1. Data

In this study, 24 sets of calibrated EEG data were prepared containing a total of 3.5 million pieces of data. Data preprocessing mainly involves data cleaning, filling in lost data, and standardizing data. The cleaning of data mainly involves removing parts with excessively low expression values, outliers, and duplicate values.

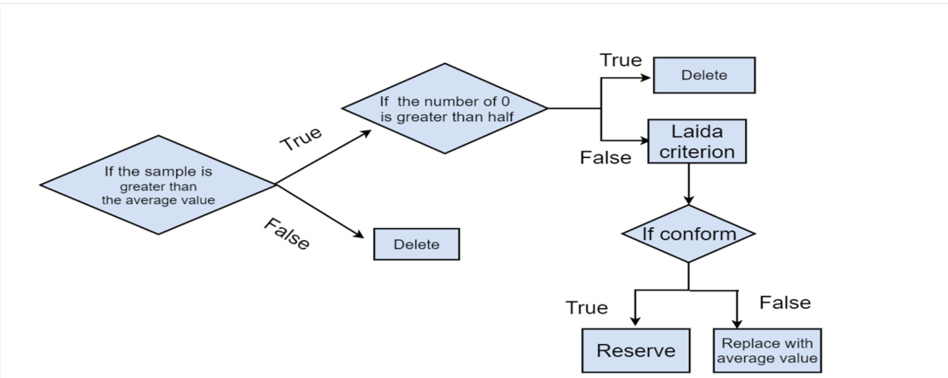

Fig. 1. Pre-processing flow chart

The main process is to determine whether the total expression amount of all samples is greater than the average value. If so, further judgment is needed to determine whether the number of 0 is greater than average. If it is greater than half, delete it as a null value. If it is less than average, use the AI model's Laida criterion, which is the 3 Sigma Principle, to determine whether it is an outlier.

For the AI model of the Laida criterion, the code block shows its operation method and assumes that a set of detection data only contains random errors, calculates, and processes them to obtain the standard deviation, and determines an interval with a certain probability. It is believed that any error exceeding this interval is not a random error but a coarse error, and data containing this error should be eliminated.

2.1.2. Mechanical Arm

In the construction phase of the robotic arm, Solidworks is considered as the model-building tool. In the subsequent testing phase, the robotic arm will be tested for multi-axis motion to ensure its stability and reliability in real-world operation. The tests will cover motions in different directions, including grasping and releasing motions, to verify the coordination between the components of the robotic arm.

In this part, brainwave data is analyzed through AI to identify the user's intent and optimize the motion control of the robotic arm based on that intent. This ensures that the robotic arm performs the required movements in a more accurate and smooth manner. At the same time, the AI can adjust the training program and range of motion in real-time based on the user's progress and performance. In this way, users can get a more personalized experience. In terms of adaptive learning, AI can perform pattern recognition and learning by analyzing data from multiple users. This helps improve the algorithm so that it can better adapt to the needs and changes of different users. In some cases, a robotic arm may need to make decisions without explicit instructions, such as avoiding obstacles or adjusting posture. AI can help the robotic arm make autonomous decisions based on the environment and the task.

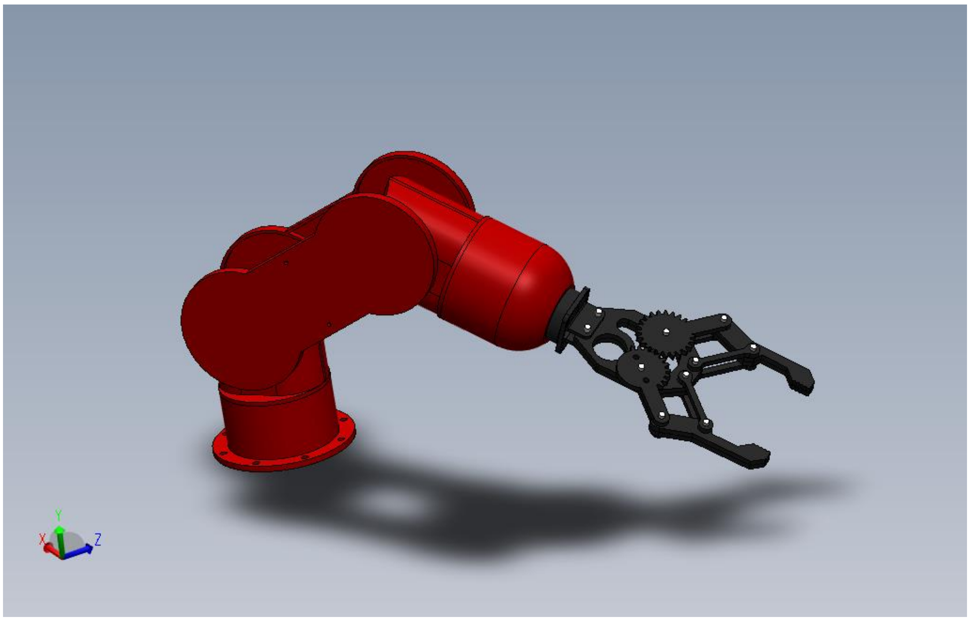

Fig. 2. Mechanical Arm

2.2. *Results*

2.2.1. Progress

In this project, a large number of EEG data based on motor imagination were processed, which were obtained from public databases and pre-processed to be converted into one-dimensional data suitable for analysis.

subject	right hand		left hand		subject	right hand		left hand	
	c3	c4	c3	c4		c3	c4	c3	c4
	298	167	176	85		279	122	372	111
12	318	162	189	144	6	278	111	381	166
	334	356	170	269		370	309	352	187
11	213	380	216	152	5	384	328	332	211
	119	165	195	201		341	318	135	137
10	132	178	190	196	4	346	290	155	133
	261	-697	547	191		238	261	321	155
9	261	-694	562	192	3	258	160	404	154
	287	179	197	209		227	197	348	317
8	284	179	190	204	2	238	192	358	319
	264	13	227	268		301	393	343	186
7	248	11	228	264	1	312	387	349	200

Fig. 3. EEG Dataset

At the same time, this data is used to train the AI model and use specific data points and analysis methods to determine the label of the EEG data that helps the user distinguish between ”left” or ”right.” At present, the project has made good progress. In order to realize the interaction with the robot arm, the interaction module of Matlab is also used, and the signal obtained by analyzing the EEG data by artificial intelligence is converted into a form representing ”0” (left) or ”1” (right) and then transmitted to the automatic grasping robot arm to help the user select and grasp operations. During the testing phase, the project achieved satisfactory results, with the accuracy of the model reaching a percentage of 80.

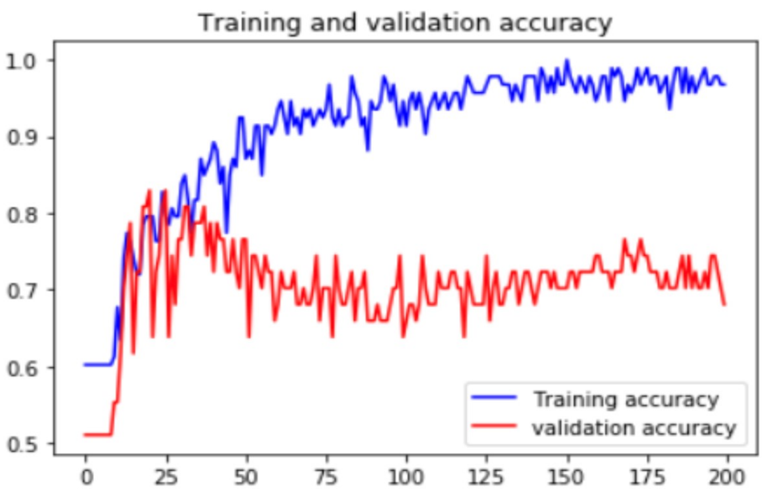

Fig. 4. Degree of Accuracy

Finally, the module successfully interacted with the trained AI model with the robotic arm and achieved deployment. After repeated experiments and optimization, the performance of the model was verified. The success of this stage means that the left and right-hand labels of EEG signals could be recognized accurately through AI technology and applied to tasks such as controlling robotic arms.

The above is an ICA independent component analysis chart before and after irrelevant components and noise removal using the sample file provided in eeglab. As can be seen from the figure, since eye noise has a great influence on channel 1, we reduced the electrical artifacts of the eye by eliminating the components of channel 1 In summary, the pretreatment plays an important role in removing useless signal bands and noise and also provides convenient conditions for the subsequent feature extraction.

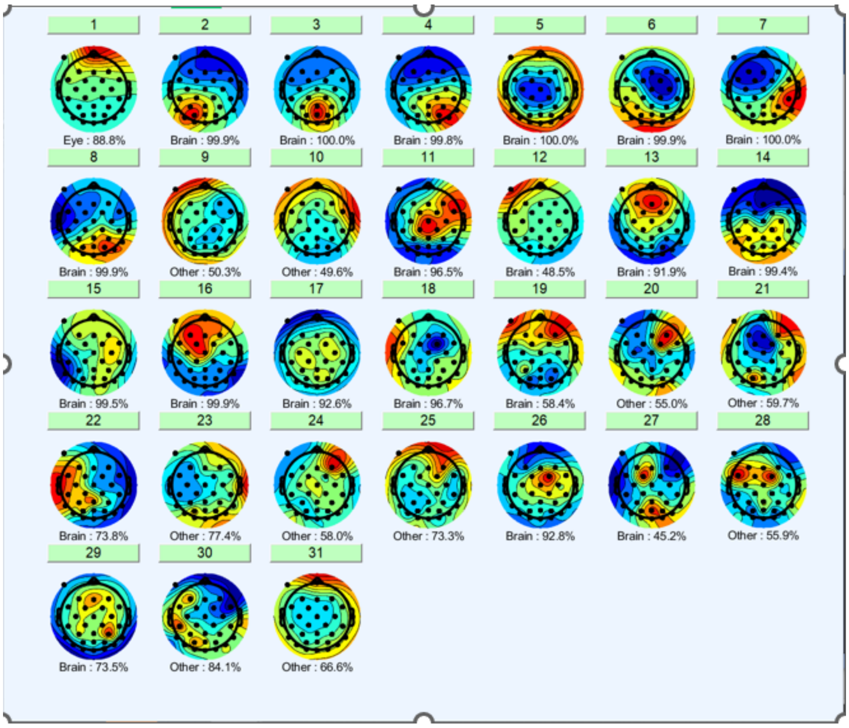

Fig. 5. Degree of Accuracy

2.2.2. Model Optimization

In addition, the project team also conducted comprehensive testing of the entire system, including integrated testing of brain-computer interfaces, signal processing, artificial intelligence models, and robotic arm movements. This is to help ensure seamless collaboration between individual modules, as well as the performance and stability of the entire system.

To further improve the accuracy of AI models, more training data should be considered, covering a wider range of users and situations. At the same time, optimizing artificial intelligence algorithms and adopting more advanced technologies may help further improve the accuracy of signal decoding and classification.

In terms of robotic arms, it is possible to consider introducing feedback control mechanisms so that the force and position can be adjusted more precisely when grasping objects. In addition, combining the robotic arm with the vision system can achieve more intelligent target recognition and object grasping, further improving the practicality of the system.

2.3. Limitations

In terms of signal processing, the reception of EEG signals is susceptible to influences from the environment and other factors, resulting in noisy or unstable signals. At the same time, EEG signals do not always accurately reflect an individual's intentions. In addition, insufficiently comprehensive processing of the signal may also lead to problems with noise in the signal. When processing EEG signals, environmental disturbances, muscle movement disturbances, and other physiological factors may introduce unwanted noise into the signal if appropriate noise filtering and correction methods are not adopted. This may affect the reliability and interpretation of the signal, and thus the results of the experiment.

In terms of data processing, the current experiments only differentiated between right and left hands, while more detailed requirements involving hand movements, for example, are more limited. The limitations of this approach may affect the accuracy of EEG signals. Indeed, the diversity of hand movements plays an important role in neural signals, and they contain richer and more specific information. Therefore, focusing only on the distinction between right and left hands may not fully capture the motor intentions and neural responses of an individual.

2.4. Conclusion

Taken together, by closely integrating EEG technology with artificial intelligence, it is possible to achieve accurate capture and interpretation of the user's brainwave signals, and through machine learning to provide labeled and unlabeled data for artificial intelligence to be trained that can automatically differentiate between EEG signals generated by the left and right hands, thus providing the user with a secondary categorization of the brainwave signals, and improving the efficiency of the classification of the signals. This technology allows the user to interact with the rehabilitation device. Real-time feedback and adaptive algorithms make the rehabilitation experience more personalized and flexible, helping patients participate more effectively in the rehabilitation process.

Despite initial successes, there are still some challenges to overcome. First, the stability and noise issues of EEG signals still need to be better addressed to ensure the accuracy and reliability of the system. Second, inter-individual variability may affect signal interpretation and rehabilitation outcomes, and thus individualized adaptation strategies need to be developed. Taken together, the EEG brainwave-controlled robotic arm represents a major step forward in the field of neurorehabilitation and is expected to bring more effective and personalized rehabilitation to patients with neurological disorders.

2.5. Discussion

2.5.1. Data Processing

In terms of data, this project successfully utilized public databases to acquire motion image data of the parietal region of the head as the primary source. The neural signals were acquired through a noninvasive brain-computer interface, and the data were preprocessed, decoded, and analyzed using MATLAB. Meanwhile, signal fragments were extracted from different channels and refined to ensure data quality. Using artificial intelligence algorithms, the "destination signal" was effectively derived, laying the foundation for subsequent artificial intelligence model training. This process utilized the potential of EEG signal data and proved to be a success for the project. It is worth noting that the externality of the brain-computer interface ensures the safety of the user and does not cause direct harm to the user.

2.5.2. Future Work

Optimizing the performance of the robotic arm and incorporating algorithms and programs into the robotic arm access is the main direction of work in the future.

In this study, brain-computer technology is integrated with the robotic arm, while artificial intelligence algorithms are injected into the data processing to improve the efficiency and accuracy of signal processing. Notably, the robotic arm model was successful in terms of coordination and motion stability. This progress introduces advanced signal processing and smarter input-output feedback systems for brain-computer interface technology and robotic arm design. In the future, this project will explore complex signal processing methods and improve the motion control algorithm of the robotic arm. It will also be combined with clinical rehabilitation training to preset the designated rehabilitation movements for the robotic arm, such as opening and closing the finger, and opening the palm of the hand to make it more in line with the clinical practical application and the personalized requirements of rehabilitation training. It is expected to be possible to realize AI-driven intelligent control to support subtle practical applications. Continued innovation will drive the product's development in sports rehabilitation, holistic health, and the broader field.

3. Project Skills

3.1. Operation Mode

During the project, a division of labor was adopted, based on the skills that each member specialized in.

In terms of project management, the project was divided into different parts, and the Gantt chart method was used to solve the problems in each part. Regular group meetings were held to share the work done by everyone. Some challenges were encountered in the project where authoritative data sources were not available at the beginning. Thanks to some members who found suitable public database databases, this problem was solved.

3.2. Personal Contributions

Aims	work	Team member
•Understand what AI is and how it affects society	Search for literature and conduct literature review	CHEN WENYI
	Extensive research has been conducted on integration methods	LI YUXUAN
	Have a good understanding of artificial intelligence and am able to process data more effectively	WANG RUIKE
	By reading relevant literature, we found the application of AI in EEG analysis and preliminarily discussed the method of establishing AI models	YAN BOHAN
•Become familiar with a variety of algorithms	Familiar with how to use artificial intelligence to process signals	CHEN WENYI
	Focus on selecting the appropriate dataset and using MATLAB for initial data processing	LI YUXUAN
	In the steps of deduplication and filling in missing values, the most valuable feature was selected	WANG RUIKE
	Using Matlab to write AI models for learning and analysis, using labeled data to t	YAN BOHAN
•Discuss applications of AI	Project leader, organizing discussions	CHEN WENYI
	Propose suggestions to collaborate mechanical design with machine learning and study for the current applications of AI and discuss the future work	LI YUXUAN
	Constructed a robotic arm with team members and simulated actual execution	WANG RUIKE
	Learned and applied the Jupyter platform to write a data preprocessing program in big data mode	YAN BOHAN

Fig. 6. Team Work

CHEN WENYI:

As the leader of the project, actively promoting the various processes of the project. Made the division of labor of the team members clear by designing the Gantt chart, and ensured that everyone could complete the goals. The work needed for the whole project mainly concerned the collection and processing analysis of data, as well as the research of machine learning methods and model training methods.

LI YUXUAN:

During data preprocessing, appropriate data sets were selected collaboratively and initial data processing was performed using MATLAB. In addition, advanced data estimation techniques were applied to deal with missing values to improve the comprehensiveness of the dataset for subsequent analysis.

In the area of machine learning, the understanding of complex ensemble algorithms was enhanced, and extensive research was conducted on integrating ensemble methods into classification tasks, exploring their potential to improve the accuracy and robustness of AI models. Within the team, proposals were made to synergize this design with machine learning and AI algorithms to optimize functionality.

WANG RUIKE:

In the data preprocessing stage, effective data was collected from public datasets, and through the steps of deduplication and filling in missing values, the most valuable features were selected for extraction, providing a better data foundation for artificial intelligence models.

In the project, a robotic arm was constructed using Solidworks through team collaboration, and its performance in real work scenarios was simulated. In the process of collaborating with the team, an understanding of the application of artificial intelligence was gained. By using various advanced algorithms and tools, data processing efficiency was improved, freeing time and energy from tedious preprocessing tasks, and allowing focus on more meaningful analysis and innovation.

YAN BOHAN:

In the data preprocessing section, applied the Jupyter platform to write a data preprocessing program in big data mode, which can effectively process a large amount of two-dimensional data delete 0 and null values, and recompiled the data into a one-dimensional format for machine learning.

In the data analysis stage, the AI model written in Matlab was used for data learning and analysis. A large amount of labeled data was fed to train the AI to find feature values and new data was constantly used to improve the accuracy of the AI. In terms of robotic arm modeling, Solidwork was used to establish an intelligent robotic arm model that could interact with the code, effectively simulating selection and grabbing functions.

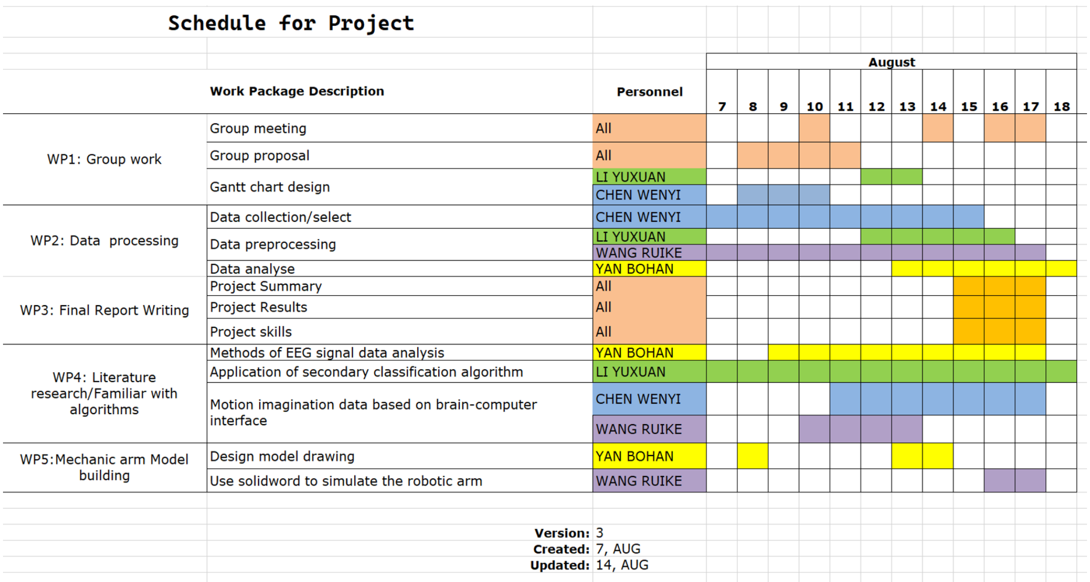

Fig. 7. Gantt Chart

Author Contributions

Conceptualization: Chen Wenyi, Wang Ruike, Yan Bohan and Li Yuxuan; methodology, validation, formal analysis: Chen Wenyi, Wang Ruike, Yan Bohan and Li Yuxuan; investigation, resources, data curation: Chen Wenyi and Yan Bohan; writing-original draft preparation, visualization: Chen Wenyi and Wang Ruike; writing-reviewing and editing, visualization and supervision: Wang Ruike and Yan Bohan; Project administration: Wang Ruike and Yan Bohan. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Research Guidelines

This study followed the research guidelines of the Sustainable Energy and Battery Technology, Cambridge Academic Program (online) 2023.

Informed Consent Statement

Not Applicable.

Data Availability

Please contact the corresponding author(s) for all reasonable requests for access to the data.

Acknowledgments

We would like to give our thanks to our faculty professors and teachers at Cambridge University for their guidance.

Conflicts of Interest

The authors declare no conflict of interest.

Intellectual Property

The authors attest that copyright belongs to them, the article has not been published elsewhere, and there is no infringement of any intellectual property rights as far as they are aware.

4. Bibliography

Rakshit, A., Konar, A., Nagar, A. K. (2020). A hybrid brain-computer interface for closed-loop position control of a robot arm. IEEE/CAA Journal of Automatica Sinica, 7(5), 1344–1360. https://doi.org/10.1109/jas.2020.1003336

McFarland, D. J., Sarnacki, W. A., Wolpaw, J. R. (2010). Electroencephalographic (EEG) control of three-dimensional movement. Journal of Neural Engineering, 7(3), 036007. https://doi.org/10.1088/1741-2560/7/3/036007

Edelman, B. J., Meng, J., Suma, D., Zurn, C., Nagarajan, E., Baxter, B. S., Cline, C. C., He, B. (2019). Noninvasive neuroimaging enhances continuous neural tracking for robotic device control. Science Robotics, 4(31). https://doi.org/10.1126/scirobotics.aaw6844