An Adaptive Control Approach for Intelligent Wheelchair Based on BCI Combining with QoO

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***Abstract*—In recent years, brain-controlled intelligent wheelchairs have received extensive attention, which combines the accessibility of the Brain-computer Interface (BCI) system with the intelligence of wheelchairs. However, current brain-controlled wheelchairs are always operated in a fixed mode. The Electroencephalogram (EEG) signals with the fixed acquisition time are analyzed without considering the state of the user, which not only increases the risk of misoperation, but seriously reduces the information transfer rate of the system. To solve this problem, an adaptive control approach for intelligent wheelchair based on BCI combining with Quality of Operating (QoO) is proposed. Firstly, the influence of motor imagery signals with different time lengths in different states on classification accuracy was analyzed using tangent space Support Vector Machine (TSSVM) algorithm. Then, the definition of QoO was introduced, which was obtained by analyzing sample entropy and power spectral density (PSD) of four kinds of EEG activities, delta, theta, alpha and beta. Finally, the acquisition time of required EEG signals was adjusted according to the value of QoO. We constructed a brain-controlled wheelchair system and conducted real environmental experiments for 9 subjects using strategies, with and without adaptive control approach. The results show that the approach proposed in this paper can reduce the risk of misoperation and increase the information transfer rate on the premise of ensuring the classification performance during navigation in complex indoor environment.**

***Index Terms*—intelligent wheelchair, adaptive control, BCI, Quality of Operating, brain-controlled**

I. Introduction

As a service robot, intelligent wheelchair has many functions such as autonomous navigation, obstacle avoidance, human-machine interaction and provision of special services, which can greatly improve the daily life and work quality of the elderly and the disabled. Brain-computer Interface (BCI) systems provide a new way to translate people's intentions into wheelchair control commands [1]. The interactive control technology of brain-controlled intelligent wheelchair is a new type of human-computer interaction technology, which can interact with the outside world independently of the brain's peripheral nerves and muscles. The study is a cross-disciplinary study in brain science, information science, and control science, which is expected to provide a new communication and control channel for patients with severe motor disabilities, expand their range of activities and improve their quality of life [2], [3], [4].

Since Tanaka et al. constructed the first brain-controlled wheelchair system [5], this technology have been greatly developed. Researchers have extracted and identified a variety of Electroencephalogram (EEG) signals in the field of brain-controlled wheelchairs, including steady state visual evoked potential (SSVEP), P300 and motor imagery [6], [7], [8]. Duan et al. proposed a two-layer shared-control strategy for brain-controlled intelligent wheelchairs based on SSVEP, which was used to generate suitable motion commands [9]. In the proposed method, the first one is a machine decision layer and the second one is a user's intention matching layer. However, the state of the user was not considered in the process of intention recognition, and the scope of intelligent control did not include changes of the user's state. Moreover, most wheelchair control systems mainly optimize signal processing and classification algorithms to improve the classification accuracy. However, these systems have poor flexibility and the risk of misoperation is extremely high. If the state of people is used as a variable, when the state is good, the time for signal acquisition is shortened; otherwise, the acquisition time is restored or the system do not issue control commands. This will increase the information transfer rate while ensuring accuracy.

The state of the user is of great importance to the wheelchair control system. Jia et al. proposed a concept named quality of teleoperator (QoT) to represent the confidence of decisions and commands generated by the teleoperator [10], [11]. They used Emotiv Epoc to generate a series of mental states, including

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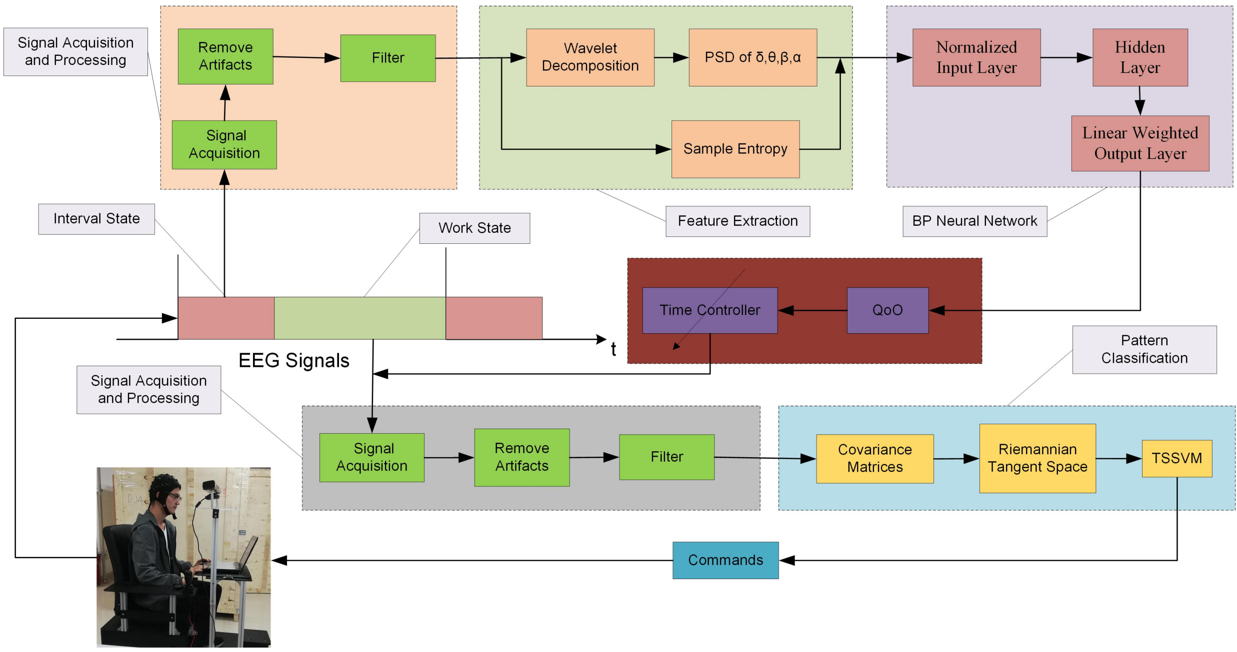

Fig. 1. The overall framework of the intelligent wheelchair system.

Long Term Excitement, Short Term Excitement, Boredom, Meditation and Frustration, then mapped these mental states to generate QoT. But it was only used in robot operating systems. In the field of driving, the fatigue state of people can also be analyzed through EEG signals [12]. The driving fatigue detection method based on EEG signals is considered to be the most reliable and promising [13]. The mental fatigue evaluation indicators based on EEG signals can be divided into linear and nonlinear indicators. The linear indicators are mainly based on the power of each rhythm [14]. The nonlinear indicators mainly include various types of entropy, complexity and correlation dimensions [15], [16]. Peng et al. proposed an objective fatigue index based on multi-scale entropy (MSE) of subject's EEG signals. But they did not use the fatigue index to adjust the BCI system for practical application [17].

It is undoubtedly a waste of resources to analyze EEG signals with the same time length in different states of the user. And operating a wheelchair in poor vigilance state is dangerous. So this paper intends to adaptively adjust the time length of EEG signals to improve the information transfer rate without reducing the classification performance. From what has been discussed above, this paper proposes an adaptive control approach for intelligent wheelchair based on BCI combining with Quality of Operating (QoO). Before classification of motor imagery signals, the user's state is analyzed to adaptively adjust the acquired EEG signal's length. On one hand, the concept of QoO is introduced. The power spectral density (PSD) and sample entropy of four EEG activities, delta, theta, alpha and beta are detected to be QoO indicators. These QoO indicators are used as inputs to BP neural network to generate QoO. Then QoO is used to be the basis for the adjustment of the acquisition time or the control strategy. On the other hand, motor imagery signals are classified by tangent space Support Vector Machine (TSSVM) algorithm, which is performed to get commands and control the movement of the wheelchair.

II. Overall System

A. System Framework

The intelligent wheelchair system designed in this paper has three main routes, including the generation of QoO, the classification of motor imaging signals, and the motion control of the wheelchair. QoO adjusts the acquisition time of motor imagery signal. The overall framework of the intelligent wheelchair system is shown in Fig. 1. We divide time into two parts, the interval state and the work state, which are used for QoO generation and motor imagery signal extraction. QoO is generated by a series of QoO indicators through BP neural network. And pattern classification is based on Riemannian tanget space and TSSVM algorithm. Finally, the wheelchair performs the control commands for movement.

B. Wheelchair Structure

We designed an intelligent wheelchair so that people with limited mobility could control it by manual remote control. At the same time, considering critically ill patients, the consciousness of the user is recognized to control the wheelchair by capturing EEG signals. The wheelchair is equipped with sensors such as binocular camera and laser radar, which enables simple path planning for the wheelchair motion. The base of the wheelchair is controlled by STM32 and the serial port of the host computer. The wheelchair structure is shown in Fig. 2.

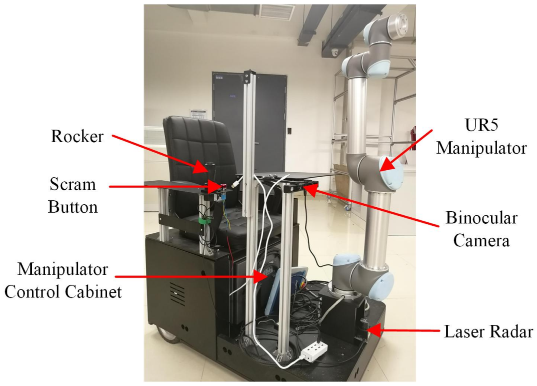

Fig. 2. The wheelchair structure. The intelligent wheelchair includes a variety of information acquisition sensors and motion controllers for path planning and grabbing objects. It can be controlled by the handle or the host computer.

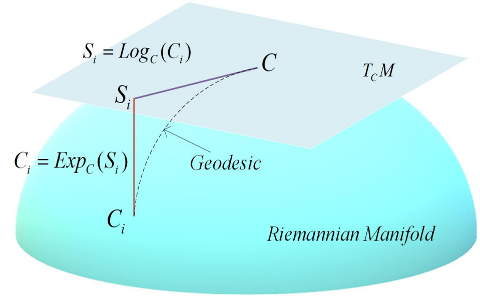

Fig. 3. The diagram of Riemannian manifold. C_i is a point in Riemannian manifold. The $T_C M$ is the tangent space based on tangent point C. Dotted line between C_i and C is the geodesic. The corresponding point of C_i on the tangent space is S_i. They convert each other through exponential mapping and logarithmic mapping.

III. Control Methods

A. Classification Algorithm

In recent years, Riemannian geometric classifier is considered to be the most promising in EEG-based BCI applications. In general, spatial filtering is a relevant process. One of the general benefits of the use of Riemannian geometry is that feature extractions are intrinsically integrated in the classification and thus spatial filtering is not needed. This is beneficial to the practical application of BCI. Barachant et al. proposed two classification algorithms called Minimum distance to Riemannian mean (MDRM) and tangent space Linear Discriminant Analysis (TSLDA) using Riemannian distance [18], which showed good classification performance.

We used the Riemannian geometry to analyze EEG signals. Assuming that the acquired EEG signal is $X_i = [x_t + T_i ... x_t + T_i + T_s - 1] \in R^{n \times T_s}$, n is the number of channels, and T_s is the number of samples. We find the Sample Covariance Matrix (SCM) as

$$C_i = \frac{1}{T_s - 1} X_i X_i^T \tag{1}$$

The SCM is located on the symmetric and positive definite (SPD) space. In order to make full use of the intrinsic information of the SCM, we assign Riemannian distance to it. The Riemannian distance is calculated by

$$\delta_R(C_1, C_2) = \left\| \log(C_1^{-1} C_2) \right\|_F = \left[\sum_{i=1}^{n} \log^2 \lambda_i \right]^{1/2} \tag{2}$$

where $\lambda_i (i = 1, ..., n)$ are the real eigenvalues of $C_1^{-1} C_2$ [19].

The SPD matrix space given by Riemannian distance is called Riemannian manifold. Riemannian manifold and its tangent space are shown in Fig. 3. The manifold is a topological space with local Euclidean space. The vicinity of each point in the manifold and an open set of Euclidean space are homeomorphic. The manifold is the result of a piece of Euclidean space sticking together. The Riemannian mean Θ can be obtained by an iterative algorithm as

$$\Theta(C_1, ..., C_I) = \underset{C \in C(n)}{\arg\min} \sum_{i=1}^{I} \delta^2(C, C_i) \tag{3}$$

In Fig. 3, the $T_C M$ is a tangent space based on the Riemannian mean. The SCM in Riemannian manifold can be mapped to the tangent space by logarithmic mapping, and can also be returned to the manifold by exponential mapping [20]

$$S_i = \mathrm{Log}_C(C_i) = C^{1/2} \log m(C^{-1/2} C_i C^{-1/2}) C^{1/2} \tag{4}$$

$$C_i = \mathrm{Exp}_C(S_i) = C^{1/2} \exp m(C^{-1/2} S_i C^{-1/2}) C^{1/2} \tag{5}$$

In order to facilitate the processing, we vectorize the matrix features

$$vect(C) = [C_{1,1}; \sqrt{2} C_{1,2}; C_{2,2}; ...; C_{E,E}] \tag{6}$$

where $\sqrt{2}$ is to ensure that the F norms are equal before and after the transformation.

Support Vector Machine (SVM) is a machine learning method developed on the basis of statistical learning theory. It is a supervised learning method originally proposed by Vapnik et al. and has rapidly developed and derived a series of improved and extended algorithms, which have been widely used in pattern recognition [21]. We combine Riemannian geometry with SVM to form the TSSVM algorithm [22]. Compute the covariance matrices of the training dataset and find the Riemannian mean. The covariance matrices are mapped to the tangent space with the Riemannian mean as the tangent point. Finally, these data are classified with a SVM classifier. The pseudo code of the TSSVM algorithm is given.

B. Quality of Operating (QoO)

The Quality of Operating (QoO) characterizes the state of the user and the credibility of the command, which is of great significance to the intelligent wheelchair system [11]. In this paper, we mainly characterize QoO by analyzing the user's vigilance. The energy of EEG signals changes with people's vigilance [23]. Take an EEG signal X_i and transform it by

Algorithm 1 Tangent Space SVM (TSSVM)

Input:

$X_i(i = 1, ..., I)$: a set of trials with different known classes; X: an EEG trial with unknown class;

Output:

$\hat{k}$: the estimated class of test trial X;

Compute SCMs of X_i to obtain C_i, (1),
Compute SCM of X to obtain C, (1),
Compute Riemannian mean Θ of the whole set, (3),
for $i = 1$ to I do
    $S_i = \mathrm{Log}_\Theta(C_i)$, (4)
end for
Compute $S = \mathrm{Log}_\Theta(C)$, (4),
Train model for S_i by using SVM classifier,
$\hat{k}$ = model (S),
return $\hat{k}$.

Fourier transform to $X(\omega_i)$, so the power spectral density (PSD) is calculated as

$$P = \frac{1}{N} X(\omega_i) \cdot X(\omega_i)^* \tag{7}$$

where N is sample length and $X(\omega_i)^*$ is the conjugate of $X(\omega_i)$.

And there is a strong relationship between sample entropy and vigilance [24]. When awake, people are in complex thinking activities and EEG signals appear very complex randomness. So the sample entropy is high. With the gradual deepening of fatigue, the activities of brain neurons gradually reduced, and the sample entropy is low. By refactoring $B^m(r)$ and $B^{m+1}(r)$ [25], we can find the sample entropy as

$$SampEn(m, r) = \lim_{N \to \infty} [-\ln \frac{B^{m+1}(r)}{B^m(r)}] \tag{8}$$

where N is the number of samples, $B^m(r)$ is the probability that two sequences match m points under a similar tolerance r, and $B^{m+1}(r)$ is the probability that $m+1$ points are matched. However, in EEG signal analysis, N cannot be ∞. So when N takes a finite value, the sample entropy is estimated as

$$SampEn(m, r) = -\ln \frac{B^{m+1}(r)}{B^m(r)} \tag{9}$$

So we extract the sample entropy and PSD as QoO indicators, and then trained them through BP neural network to obtain QoO. The QoO generation process is shown in Fig. 4. The designed BP neural network consists of three layers [26]: a normalized input layer, a hidden layer and a linear weighted output layer. The neural network inputs are a series of QoO indicators, each of which is represented as a scalar variable and normalized to [0, 1]. The neural network output is QoO.

In order to quantify the value of QoO and evaluate the experimental tasks, we use the entropy weighting method to assign a weight to each task indicator [27]. The entropy weighting method uses information entropy to evaluate the level of order and the utility value of the system information. The higher the level of order of an indicator, the smaller its entropy value, and the higher the effectiveness of comprehensive evaluation. Each task indicator is treated as a system. Suppose there are n indicators, and the number of samples of each indicator is m. The specific data of each sample about this indicator is $y_{ij}(i = 1, ..., n; j = 1, ..., m)$. So the unit entropy value of the system is as

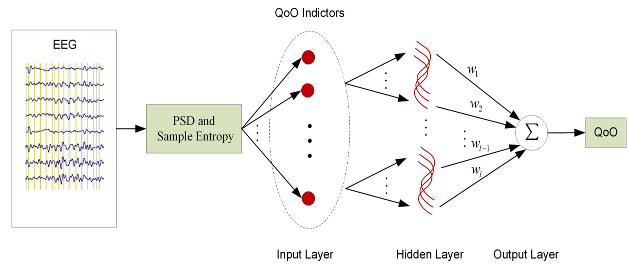

Fig. 4. The QoO generation process.

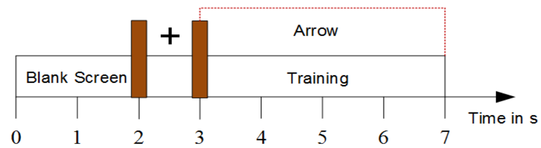

Fig. 5. The timing of the paradigm.

$$e_i = -k_i \sum_{j=1}^{m} y_{ij} \ln y_{ij} \tag{10}$$

where $k_i = 1/\ln m$. If y_{ij} is 0, 0.00001 is used instead of calculation.

So the information utility value of each indicator depends on the difference between the entropy of the indicator and 1

$$d_i = 1 - e_i \tag{11}$$

The higher the utility value, the greater the contribution to the evaluation results. Therefore, the weight of each indicator in the comprehensive evaluation is the proportion of its information utility value in the total of all indicators

$$w_i = d_i \Big/ \sum_{i=1}^{n} d_i \tag{12}$$

So QoO is calculated as

$$QoO_j = \sum_{i=1}^{n} y_{ij} w_i \tag{13}$$

IV. Experiments and Results Discussion

A. Experimental Setup

Nine healthy subjects (eight males, one female, marked as s1-s9, aged 23 to 26, right-handed) participated in the experiments. All experiments were completed in a quiet laboratory and included offline classification experiment, QoO model generation experiment, and adaptive control experiment.

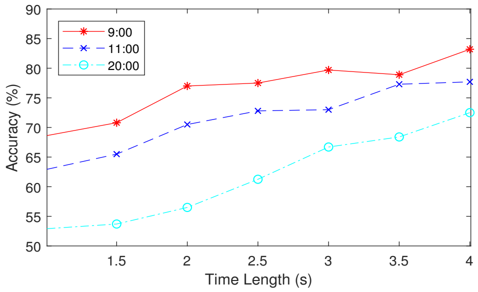

Fig. 6. The cross-validation classification results of different time length's EEG signals with the TSSVM algorithm.

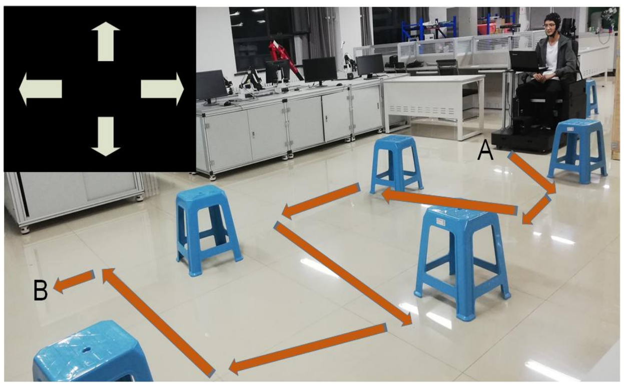

Fig. 7. Schematic diagram of the experimental task.

The experiment time was set to 9:00, 11:00 and 20:00 respectively, which represented that the state of subjects was awake, light fatigue and fatigue. The recording was made using NeuroScan NuAmps amplifier and EEG acquisition cap. In order to facilitate analysis, we only used C3, C4, FC4, Cz and CPz for classification experiments, F3 for QoO generation experiments, and A1 and A2 as reference channels [28]. The subjects sat in the wheelchair and performed motor imagery of left hand, right hand, tongue and feet according to the arrows: left, right, up and down. All subjects signed an informed consent before experiments.

B. Offline Classification Experiment

In the offline classification experiment, each subject completed 12 trials (3 times per arrow) in each time period. All trials were divided into three groups according to time and each group contained 108 samples. The subjects remained quietly ready for 2s before the experiment. In the 2nd second, '+' appeared on the screen. At the 3rd second, the left, right, up or down arrows were displayed, and the subjects followed the prompt to perform motor imagery of left hand, right hand, tongue and feet until the end of the 7th second. The timing of the paradigm is shown in Fig. 5. Signals were removed ocular artifacts and band-pass filtered into 7-30Hz.

We separately intercepted EEG signals with time lengths of 4s, 3.5s, 3s, 2.5s, 2s, 1.5s, and 1s of each group and used the TSSVM algorithm for classification. The cross-validation results are shown in Fig. 6. As can be seen from Fig. 6,

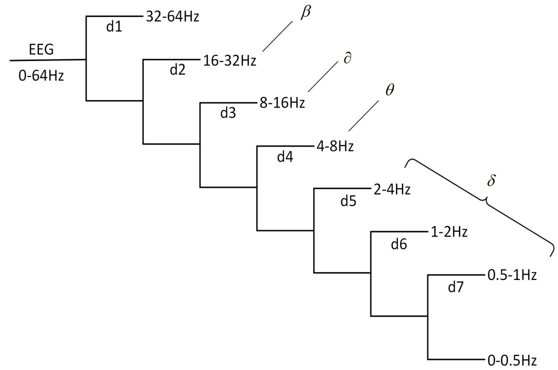

Fig. 8. The wavelet decomposition diagram.We used the demy function to perform 7-layer wavelet decomposition, then reconstructed d7, d6 and d5 to get δ wave (0.5-4Hz), reconstructed d4 to get θ wave (4-8Hz), reconstructed d3 to get ∂ wave (8-16Hz), and reconstructed d2 to get β wave (16-32Hz).

the 9:00 group has the highest accuracy, followed by the 11:00 group, and the 20:00 group has the lowest accuracy. This shows that when the fatigue level of subjects increases, the performance of motor imagery is not good. In the 9:00 group, the classification accuracy with time length 2s is still relatively high. The 11:00 group and the 20:00 group reaches the highest with time length 4s, and the accuracy rate decreases significantly with the shortening of time. It can thus be concluded that when the subject is in a good state, the acquisition time of EEG signals can be shortened to speed up the information transfer rate; when the state is not good, priority must be given to ensure accuracy to reduce misoperation.

C. QoO Generation Experiment

In order to obtain the QoO generation model, the following experiment was designed. The experimental task was to drive the wheelchair from point A to point B through motor imagery, as shown in Fig. 7. Each subject completed 10 tasks in each time period. The EEG signals of the subjects were acquired for 30s at the beginning of each task. When the task was completed, the task completion time, the number of collisions and a subjective assessment of their states (1-10 points) were recorded. The three task indicators are calibrated to QoO using the entropy weighting method and normalized to [0, 1].

We removed the artifacts such as ocular artifacts and powerline interference from the EEG signals acquired in each task, and down-sampled them to 128Hz. Then four kinds of rhythm waves were obtained through wavelet decomposition [29], as shown in Fig. 8. The PSD of these four rhythm waves and sample entropy of the EEG signals were calculated as QoO indicators. The QoO indicator distribution diagram is shown in Fig. 9. As can be seen from Fig. 9, the distribution of QoO indicators has certain regularity. Finally, we used these QoO indicators as the inputs of the neural network, and used QoO as the output to obtain the QoO generation model. And we divided the data set into training and test set to prevent overfitting.

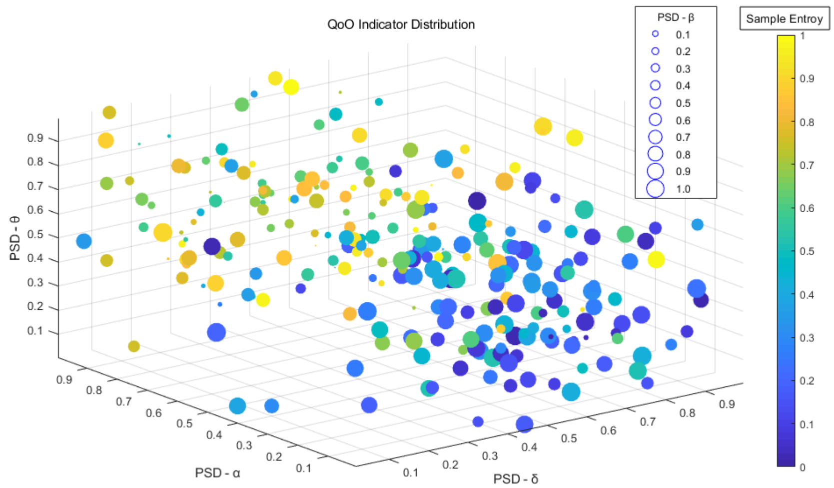

Fig. 9. The distribution of QoO indicators. The three-dimensional coordinate system represents the PSD of δ, θ, and α, the bubble size represents the PSD of β, and the color represents the sample entropy.

D. Adaptive Control Experiment

We established an adaptive control model that dynamically adjusted the EEG signal acquisition time according to the value of QoO, as shown in (14).

$$T = \begin{cases} 2, & QoO \geq H \\ 2 \times (1 - \frac{QoO-L}{H-L}) + 2, & L \leq QoO < H \\ NaN, & QoO < L \end{cases} \tag{14}$$

We set $H = 0.7$ and $L = 0.3$ in this experiment. When $QoO \geq H$, the acquisition time was set to 2s; when $L \leq QoO < H$, the acquisition time was dynamically adjusted between 2-4s; when $QoO < L$, it indicated that the current state of the user was not suitable for operating the wheelchair, and no control command was sent at this time.

The adaptive control model was added to the intelligent wheelchair system. In order to verify the effectiveness of the proposed adaptive control model, we designed the following experiment. Subjects s1-s9 participated in the experiment and the experimental task was also shown in Fig. 7. Each subject performed three times. The next trial started after the wheelchair executed the previous command. We collected the time required to complete the task, the number of collisions and the number of control instructions generated. At the same time, it was compared with the wheelchair system without the adaptive control model. Fig. 10 shows the experimental results.

Through data comparison, we found that the numbers of collisions and the number of control instructions generated with adaptive control model are slightly less than that without it, and the task completion time with the adaptive control model is 35.16s shorter. We also counted the confusion matrix of EEG signal recognition in all trials, as shown in Fig. 11. The recognition accuracies are 74.13% and 75.26% with and without the adaptive control model. This shows that our adaptive control model can greatly shorten the task completion time and increase the information transfer rate on the premise of ensuring the classification performance.

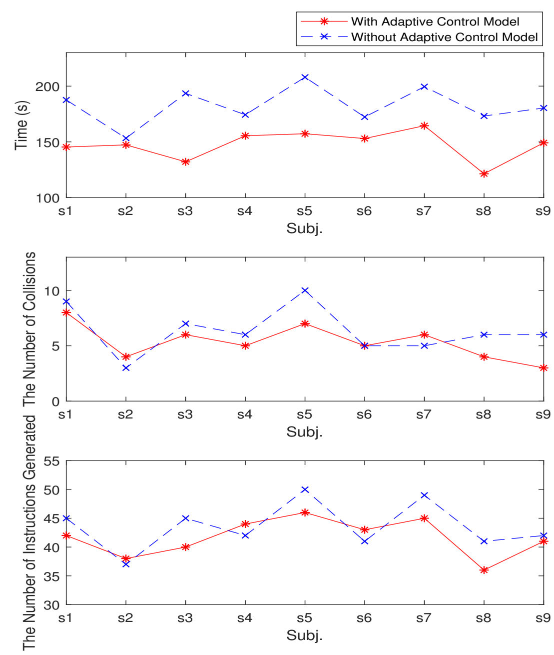

Fig. 10. Comparison of experimental results.

V. Conclusions

In this paper, we proposed an adaptive control approach for intelligent wheelchair based on BCI combining with QoO, which adaptively adjusts the acquisition time of EEG signals. And we validated the method through online experiments. This

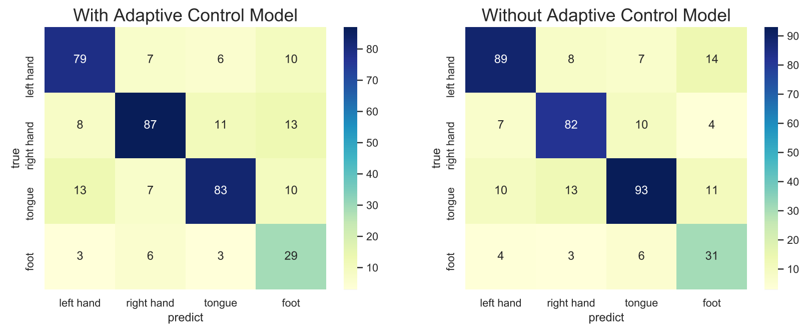

Fig. 11. The confusion matrix of EEG signal recognition in all trials.

adaptive control approach increases the flexibility and stability of the system. The main research results in this paper are as follows:

- We analyzed the TSSVM algorithm and classified EEG signals to obtain the minimum time required for motor imagery.
- We established a neural network model that obtained the user's Quality of Operating (QoO) from the EEG signals, which quantify the user's vigilance state with a value.
- We established a model for adaptively adjusting the acquisition time of EEG signals, and built an intelligent wheelchair system for online verification.

The intelligent wheelchair system is a complex system involving knowledge of multiple fields. Although the method proposed in this paper has certain effectiveness, it still has a long way to go before it can be applied. In the future work, on one hand, we should improve the effectiveness of the classification algorithm, and explore various characteristic metrics of user, not just vigilance; on the other hand, we need to improve the reliability and practicability of the hardware equipment.

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