Automatic
Control &
Systems
Engineering.

# Control the wheelchair based on the motor imagery and BCI technology

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# ABSTRACT

Brain-computer interface (BCI) can help people with severe motor disability to control a device only using their thoughts. Two classes of motor imagery, mainly imagination of movement of right and left hand, have been commonly used to control the BCI. However, in many BCI applications more than two commands are required to control the system.

The Common Spatial Patterns (CSP) algorithm can classify 2-class imagery, recorded using electroencephalogram (EEG) data. To be able to have a BCI system being control with four classes of motor imagery, this thesis developed two extension of the CSP, namely, Pair-Wise (PW) and One -Versus-Rest (OVR) compare the final accuracy of the two methods. Paired t-test showed there was no significant difference between the two methods.

# ACKNOWLEDGEMENTS

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# Chapter 1 - Introduction

## 1.1. Background and Motivation

With the rapid progress of biotechnology and computer technology, as well as scientists' gradual in-depth study of the functional field of the brain, "Brain-Computer-Interface Technology" Brain-Computer-Interface (BCI) has slowly attracted widespread attention in the scientific community. Since 1929, the scientific community first proposed the concept of EEG signals. People gradually understand that when humans undergo emotional changes and try to perform certain actions, the human brain will also generate certain biological signals accordingly. Of course, the biological signals produced by the left and right brains when thinking or reacting under different thinking modes are also different. But the most important point is that these signals can accurately reflect people's thoughts or next intentions and send biological signals to the muscles through the human nervous system and complete the control of the body's movement. This physiological system is very similar to the computer and its control system, so scientists have been trying to create a system that can completely simulate the human body. This system can easily obtain the brain electrical signals of the human brain and directly convert them into digital signals or electrical signals, thereby realizing the control of external mechanical and electrical equipment. With the development of computer science and material science, people began to combine brain electrical signals with computer technology and communicate with computers through the imagination of the human brain. At present, the biggest known breakthrough of BCI technology is that many research institutions around the world have been approved to conduct microchip cerebral cortical implantation tests on patients with normal brains, through the changes in the brain electrical signals of people’s brains. To control the device in the device.

BCI technology has a history of more than 50 years since its development in the 1970s. More and more people have joined this field, and scientists around the world have set off a great wave of research. As the research content continues to deepen, scientists in more and more fields have joined in, because BCI technology involves a very large scientific field, such as biology, psychology, computer science, and so on.

To promote better development in the field, the BCI Association often holds international seminars. ("Brain-computer interface technology: A review of the Second International Meeting," 2003). The seminar attracted academic enthusiasts from various countries all over the world.

## 1.2. Problem Definition

As we all know, due to various reasons, many people are unable to walk normally and freely, and they need wheelchairs. How to ensure wheelchairs at this time Simple operation and safety have become the top issues.

Currently, MI BCI is mainly applied to 2 classes, so nowadays, MI BCI technology can be used to easily control the forward and backward of the wheelchair through human imagination. But nowadays, people's demand for wheelchairs is not only to move forward and backward but buyers and users pay more attention to the operability and experience of using smart wheelchairs. To be able to replace or get closer to the way of human activities, the operation of the wheelchair is more convenient and safer. We need more instructions to control the wheelchair. In this experiment, we give four instructions to the smart wheelchair, which are going forward, stop, turning left, and turning right, which corresponds to the movement of the feet, tongue, left hand, and right hand of the wheelchair user. 4 commands are needed， so a multi-class MI BCI is needed. From another perspective, The Common Spatial Pattern (CSP) algorithm can classify 2-class motor imagery e (EEG) data, but this design needs to use 4 classes to classify the data with 4 classes.

# 1.3. Aims and Objectives

Project Aim

This design helps those who suffer from diseases or lose the ability to walk due to accidents to sit in a wheelchair, operate the wheelchair through consciousness, and move to the position they want. The wheelchair is controlled by collecting the user's imagination that the fingers of his left and right hands point to different directions or different postures of the arms

Project Objectives, to be described as:

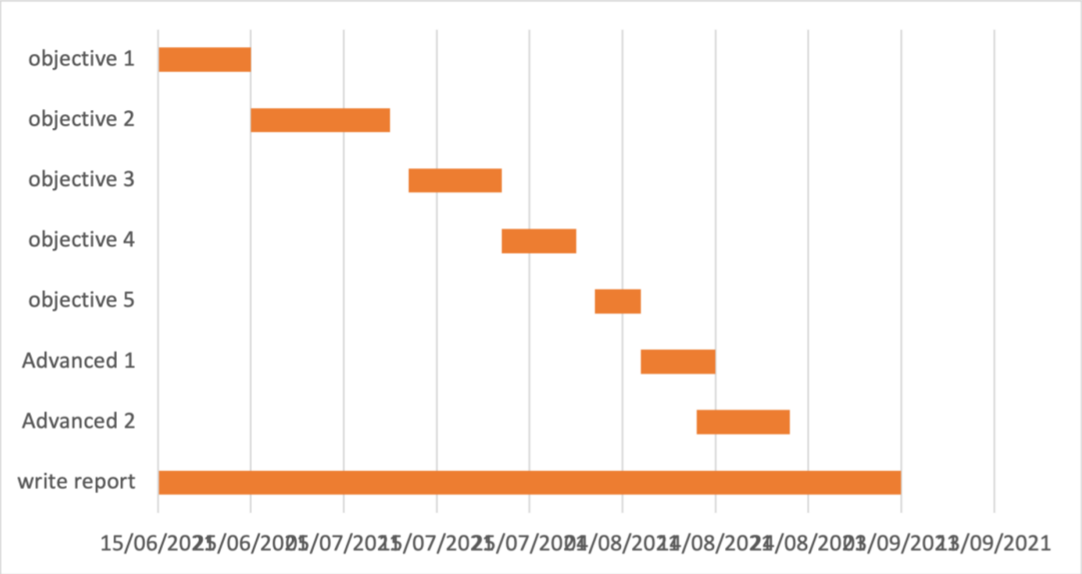
Basic Objectives:

1. Collect highly informative motor imagery data and makes classification algorithms through the data collected.
2. Use the EEGlab toolbox to process EEG signal data in Matlab.
3. Use the CSP algorithm to extract discriminative features from two different conditioned brain signals—generally.
4. Simple classification of training data using FLDA or SVM.
5. Import the processed data into the model to check whether it can be achieved.

Advanced Objectives:

1. Can be implemented in an environment with partial interference.
2. Reduce as much as possible the response time between human-computer interaction during use

## 1.4. Project Management




The design is planned to start Objective1 on June 15, 2021, for 10 days. Afterward, we will proceed to Objective2, which is expected to be completed from June 25, 2021, to July 10, 2021. Afterward, Objective3 will be started, until July 20th. Objectives 4 and 5 are expected to end before August 14, 2021. Work on advanced 1 and 2 started on August 24. The overall work process conforms to the time allocation in the Gantt chart. However, during the implementation of advance1 and 2, it was discovered that the most important thing for smart wheelchairs is how to classify 4-class data. Therefore, certain adjustments have been made to advance1 and 2 in the process. And the time to complete the thesis has been extended. The writing of the thesis started on August 15, 2021, and the writing of the thesis was completed on September 10, 2021.

# Chapter 2 - Literature review

## 2.1. Definition of BCI and BCI applications

BCI is a technology dedicated to neuroscience that can be used to measure and collect data during brain activity and transmit these brain data to a computer. And use these obtained data to complete various tasks on the operating system, such as operating the computer, controlling the smart wheelchair, controlling the prosthesis, activating the muscles, and moving certain markers on the operating system by outputting on the computer(Kögel, Jox and Friedrich, 2020). The collected brain data can be when the object is imagining the movement of a certain part of the body, when the auditory perception changes, when the sense of smell changes, when the sense of touch changes, when the visual discovery changes, when the mood changes, or when performing mental activities(IET CONTROL, ROBOTICS AND SENSORS SERIES 114 Signal Processing and Machine Learning for Brain-Machine Interfaces, no date). The data signal can be collected by implanting a chip into the brain, or it can be collected outside the brain. The most common method is the EEG method. EEG collects signals by placing electrodes on the surface of the skull(Graimann Bernhardand Allison, 2010). As shown on the side A of Figure 1, the first step of BCI technology is to collect human brain signals, and then classify and selectively process the collected signals. Then turn it into instructions that computers and machines can recognize and input them into the controlled computer or machine. Realize the control of the machine or computer through the imagination movement or operation of the brain.

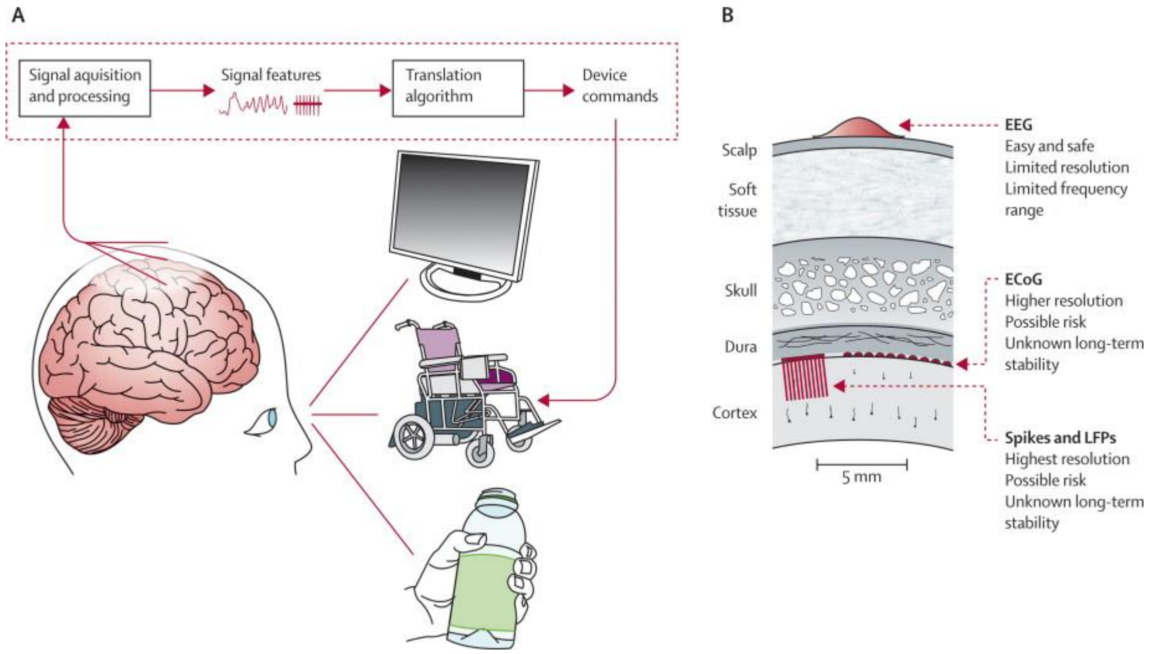



Figure 1: Figure A on the left explains the basic method and process of BCI technology implementation. Figure B on the right explains the method of collecting human brain signals, which are generally divided into two methods: non-embedded (EEG) and embedded (ECOG, Spikes and LFPS) (Daly *et al.*, 2006)

At present, the development of BCI technology is not in a very mature stage. Due to the limitations of various factors, the research results that have been developed so far have not been applied in real life, and many of them are in an exploratory stage. But from the perspective of application value and scientific value, the development of BCI technology has very important significance. Its existence can greatly promote the field of human cognition. At present, it is known that the main direction of brain-computer interface technology is to reconstruct the motor function of the human body for patients who have lost or impaired motor ability. Apply BCI technology to solve the trouble and trouble caused by patients who have lost or impaired athletic ability because of their lack of athletic ability and cannot complete some basic exercises or actions. However, the development direction of BCI is not limited to helping patients to repair their exercise ability.

(1) Medical field

As it appeared in the movie "Captain America 3", Iron Man's police friend James Roddy was unable to walk like a normal person due to accidental reasons. We can see it in "Avengers 3" afterward. James Roddy regained the ability to walk under the support of a machine in a way similar to a "neural prosthesis". Similarly, there are related technologies that use BCI technology to control smart wheelchair applications through imagination and use BCI technology to control the movement of external prostheses through imaginary movements. For patients with muscle atrophy, spinal cord injury, brain injury, etc., completely lose their mobility. At this time, the role of the brain-computer interface is revealed. The brain-computer interface can interpret brain electrical signals to help patients control external machinery and equipment through their imagination of movement. To a certain extent, it helps them rebuild motor function and improve their quality of life. In 2014, Japan's International Institute of Electrical and Communication Technology and Keio University, and other institutions jointly developed a network-based BCI system that monitors the human's blood pressure and changes in brain electrical signals to monitor human emotions and mental activities. Make judgments and guesses. And the system can relate to other machinery to achieve the function of controlling the operation of the machinery. The invention can connect the human brain with external mechanical systems, help the elderly and the disabled complete basic movements and behaviors, and provide a great convenience for their daily lives. Neuralink is an American company that researches neurotechnology and brain-computer interface technology. It was founded in 2016 by Elon Musk and eight other co-founders, dedicated to researching the technology of implanted chip-based brain-computer interfaces. In July 2019, the company revealed to the outside world that it had successfully developed a brain-computer interface system and successfully tested it on mice and monkeys. One monkey can control the movement of the computer and the cursor through its brain. The company said it may start human clinical trials in 2020. And on August 29, 2020, another pig implanted with its company chip was successfully displayed. The Neuralink device successfully read the pig's brain activity. Metz, Rachel (August 28, 2020). "Elon Musk shows off a working brain implant — in pigs". *CNN*. Retrieved October 4, 2020. Neuralink is developing a fully implanted, wireless, high-channel count brain-machine interface (BMI) with the goal of enabling people with paralysis to directly use their neural activity to operate computers and mobile devices with speed and ease. In medical medicine, BCI is also used to help patients recover their exercise capacity(Zafar, Shah and Malik, 2017). For example, to help patients with spinal cord injuries perform physical and nerve treatment and recovery, to help stroke patients recover their motor ability in the later stage, to help epilepsy patients to treat, and even to help people with mental illness to regulate (Maksimenko *et al.*, 2017).

（2）Traffic field

An American scientific research institution once reported that it proposed to use human thinking to control the movement of helicopter models and avoid obstacles. Through the signal sent by the human brain, the helicopter aircraft model is controlled (Jamil *et al.*, 2021). It can realize the stable flight of the model aircraft, and flexibly avoid multiple obstacles in this state.

（3）Emotion recognition

Because EEG signals are closely related to the functional activities of the human brain, more and more psychological studies have introduced EEG-related technologies. Many studies have shown that with the change of human emotions and mental activities, the pattern of EEG signals will also change, so it is feasible to use EEG signals to identify and record human emotions and mental activities. And the use of EEG signals to recognize emotions in psychology has also received more and more attention.

（4）Fatigue detection

Fatigue is a natural physiological state that occurs after a lack of sleep or interruption of the circadian rhythm. Fatigue can cause people to lose concentration and slow down their reactions. When driving vehicles or operating dangerous heavy machinery, fatigue often leads to serious consequences. According to a survey in New Zealand, the proportion of traffic accidents caused by fatigue is 65% (AlZu'bi, Al-Nuaimy and Al-Zubi, 2013) With the deepening of research, EEG is widely used to detect central nervous system changes. People can measure the fatigue degree of the testee through the change of the EEG signal of the human brain. Especially in recent years, the problem of fatigued driving has gradually become a hot issue in people's lives, and the technology of EEG signal acquisition has become more mature. The research of using EEG signals to detect the degree of human fatigue has been developed rapidly and has achieved good results.

（5）Housing and home furnishing

BCI technology can also be applied to smart homes. With the advancement of technology, people's quality of life has also undergone earth-shaking changes, and smart home control systems have become a hot topic. The emergence of smart homes has brought convenience to people's lives. Similarly, the application of BCI technology can also target the disabled or patients with impaired sports ability, using smart homes to bring technical assistance to their lives and improve their quality of life.

## 2.2. EEG and Motor imagery-based BCI

Electroencephalogram (EEG) is the use of bioelectric signals to monitor the brain. This technology is used to record the potential activity of the scalp above the brain. The changes in brain signals can be measured indirectly. The measurement of the EEG signal is often performed by placing electrodes on the scalp that collect the signal. Normally, there is no need for an external implantable chip. However, there are also implantable electrodes, which can be implanted into the subject in the form of a chip, sometimes referred to as intracranial EEG.EEG measures voltage fluctuations caused by ionic currents in brain neurons (Lopes da Silva, 2004). EEG is a term used in medicine to describe the recording of spontaneous brain activity across time using several electrodes on the head. The most prevalent application of EEG is to identify epilepsy, which can result in aberrant EEG results (Tatum, 2014). It can also be used to detect sleep problems, anesthetic depth, coma, encephalopathy, and brain death. EEG was formerly the gold standard for detecting tumors, strokes, and other brain disorders. Motor Imagery (MI), as the name implies, when a person imagines the movement of his limbs (or muscles) but has no actual motor output, certain brain areas of the person will still be activated. By analyzing EEG signals, detecting and recognizing the activation effects of different brain regions to determine user intentions, direct communication, and control between the human brain and external devices are realized. At present, the common imaginary parts of the movement are left and right, right hand, feet, and tongue. (Tangermann *et al.*, 2012). The side B of Figure 1 explains the methods of collecting human brain signals, which are generally divided into two methods: non-embedding (EEG) and embedding (ECOG, Spikes, and LFPS). The collection of non-embedded methods is more convenient and safer, and the cost is lower. However, the collected brain data may have large errors. Because it is an external device, it is more likely to be interfered with by the outside world during data collection. The embedded method has a greater impact on the safety of the test object. But the collected data results are more accurate, and there are less interference data. It can be seen from Figure 2 that MI BCI technology extracts and processes the EEG signal generated when the human brain imagines a certain action and sends the processed signal to the machine to achieve the purpose of controlling the machine.

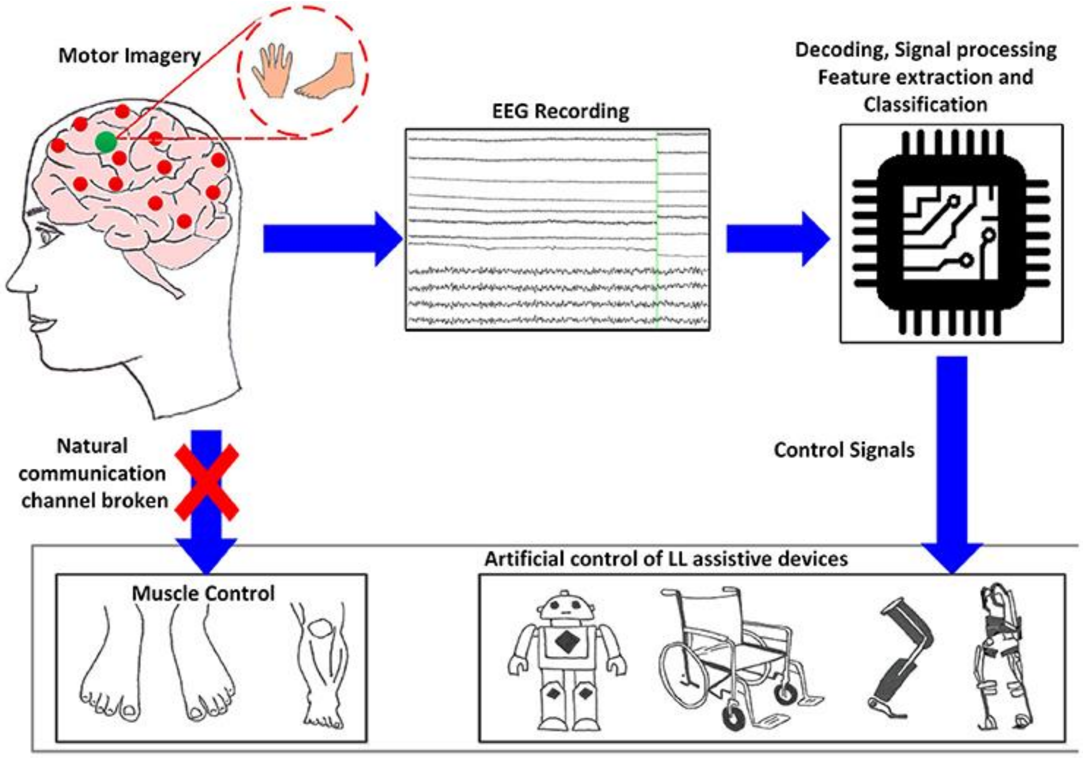



Figure 2: MI BCI technology principle (Tariq, Trivailo and Simic, 2018)

## 2.3. Classification of motor imagery BCI and challenges in classification of motor imagery based BCI

There are many types of MI BCI, but the most widely used method is to use Common spatial pattern (CSP) method and Support Vector Machine (SVM) to classify MI BCI. The Common Spatial Pattern (CSP) algorithm is an effective and popular method for classifying 2 types of moving image electroencephalogram (EEG) data. Support vector machines are essentially two types of classifiers, which generally can only solve 2 Class problems, and if the size of the training sample set is too large or extremely unbalanced, it will seriously affect its training and classification effects. The significant inter-subject heterogeneity in terms of the characteristics of the brain signals is a problem in Motor Imagery-based BCI (MI-BCI), which converts the mental image of movement to instructions(Blankertz *et al.*, 2008). The brain-computer interface (BCI) provides the connection between the human brain and the computer. The task of distinguishing the four classes of motor imagery movements (left and right hands and feet) of simple limb-based BCI is still challenging because most hypothetical movements in the motor cortex have tight spatial representations (Mohamed *et al.*, 2018).

# Chapter 3 - Methodology

## 3.1.Experiment and Dataset description

All the experimental data involved in this design are from the 2008 brain-computer interface competition data set Data sets 2a. The School of Cognitive Science, Graz University of Technology, Austria provides all the data for this data set, and the process of collecting signals In, all the signals are completely recorded during the implementation of the BCI system in the field. The subjects of the experiment were 9 healthy people, and their data were collected separately. During the whole process, the person under the test needs to imagine their feet, tongue, left hand, and right hand for four kinds of motor imagery. Everyone who accepts the test needs to conduct a two-day data collection test, and finally get the collected training data and test data.

### 3.1.1. Experimental paradigm

This data collection contains EEG data from nine different people. Four distinct motor imagery assignments were used in the cue-based BCI paradigm. nine experimenters imagine and collect the four types of movements of the left hand, right hand, feet, and tongue, and finally, get EEG data. Two data collections were performed for each participant in the experiment on two different dates. Each data collection consisted of 6 runs, with a short break between each run. A run contains 48 tests (12 tests for each of the four categories), and a total of 288 tests were performed for each data collection. Before the start of each data collection, to exclude the influence of EOG on the data results in the experiment, a relevant eye movement of about 5 minutes will be performed and the data will be recorded. Related eye movements include three parts (1) looking at the signs on the screen given for 2 minutes (2) closing your eyes for one minute (3) one minute of eye movements. The process can be seen in Figure 3

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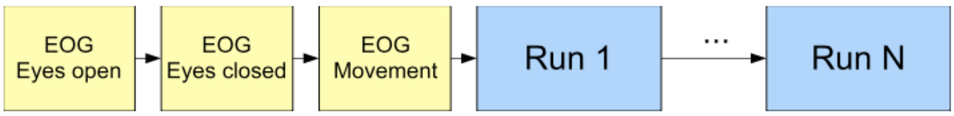


Figure 3: Timing scheme of one session.

The person undergoing the experiment sits on the chair provided by the experiment and looks at the computer screen provided by the experiment. As a reminder, at the beginning of the experiment, the screen will sound a warning, and the experimenter should watch the cross sign appearing on the screen. After two seconds, the screen will appear up, down, left, and right in sequence according to the same time interval. Two arrow instructions are indicating the direction. The instructions in the four directions represent the tongue, feet, left hand, and right hand respectively. The time for each instruction to appear and stay is 1.25 seconds. During this period, the subject needs to perform the required motor imaging tasks until there is no command on the screen to stop, and the screen turns black. Currently, the experimenter enters a short rest period, and then the same mark in the above process starts to appear on the screen again, prompting the experimenter to start the next set of experiments. Each part of the collection includes 6 independent processes, and each process has a total of 12 times of one-class motor imagery. Therefore, after the 4 classes of motor imagery collection are completed, a total of $4 \times 12 \times 6 = 288$ data will be collected for each test. The process is shown in Figure 4.

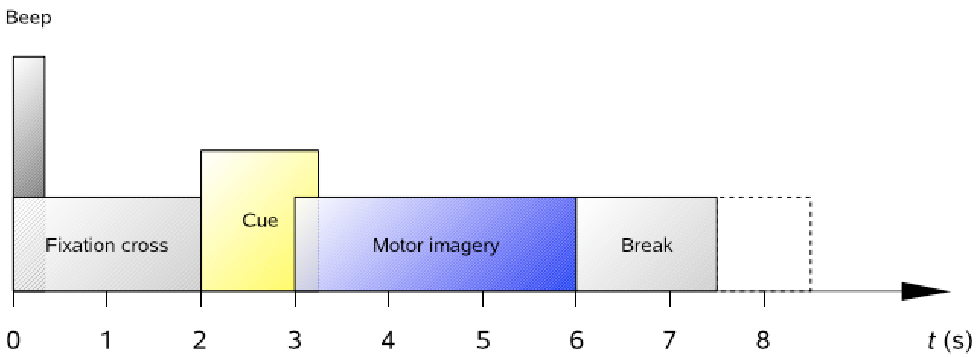


Figure 4: Timing scheme of the paradigm.

### 3.1.2. Data recording

In this experiment, 22 electrodes（EEG channels） are used to record EEG data during the data acquisition phase. As shown on the left side of figure 5 below, for the acquisition signal, we keep the signal at 250Hz for sampling. After that, we performed a bandpass filter ranging from 0.5 Hz to 100 Hz. Set the sensitivity of the amplifier (100μV). To suppress line noise, a 50 Hz notch filter is additionally enabled.

In addition, we also need to collect EOG signals. Here we use three electrodes（EEG channels） to collect EOG signals, that is, three EOG channels. As shown on the right side of figure 5 below, for the acquisition signal, we will keep the signal at 250Hz for sampling. Then perform band-pass filtering, ranging from 0.5 Hz to 100 Hz. Set the sensitivity of the amplifier (1 mV). The EOG channels are provided for the subsequent application of artifact processing methods and must not be used for classification.

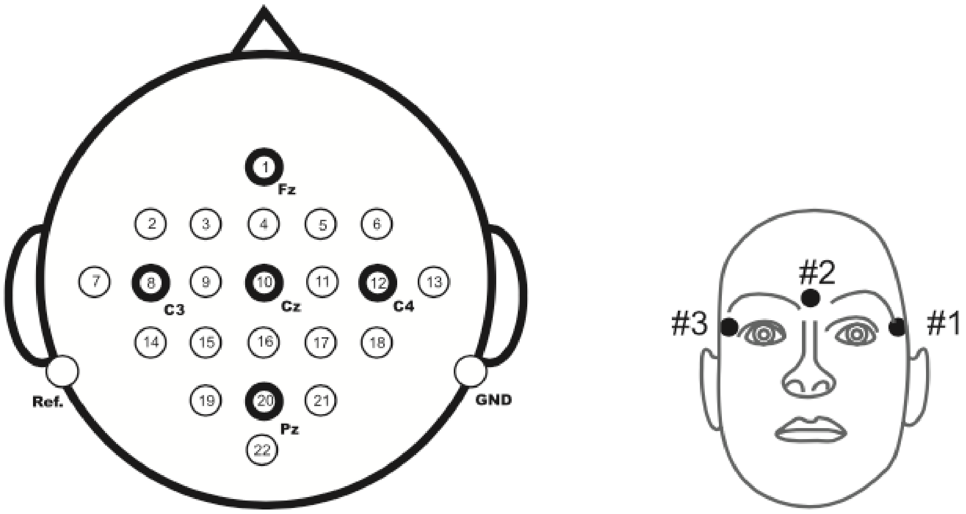


Figure 5: Left: Electrode montage corresponding to the international 10-20 system. Right: Electrode montage of the three monopolar EOG channels.

### 3.1.3. Data file description

The General Data Format for Biomedical Signals (GDF) is used to store all data sets, with one file per person and session. BioSig toolbox is an open-source toolkit, it can be used to load GDF files. After the installation is complete, IN MATLAB, load and extract the data given by the contest by executing the command [s,h]=sload('A01T.gdf'). After executing the command, there will be 2 types of sub-files in the MATLAB workspace. The first type is the data file of the collected signal, and the second type is the data structure file. (Brunner *et al.*, no date) The data structure file includes the starting point, rest time, and duration of the collection And other information.

| ID | Training | Evaluation |
|---|---|---|
| 1 | A01T.gdf | A01E.gdf |
| 2 | A02T.gdf | ~~A02E.gdf~~ |
| 3 | A03T.gdf | ~~A03E.gdf~~ |
| 4 | A04T.gdf | ~~A04E.gdf~~ |
| 5 | A05T.gdf | ~~A05E.gdf~~ |
| 6 | A06T.gdf | ~~A06E.gdf~~ |
| 7 | A07T.gdf | ~~A07E.gdf~~ |
| 8 | A08T.gdf | ~~A08E.gdf~~ |
| 9 | A09T.gdf | ~~A09E.gdf~~ |

Figure 6: List of all files contained in the data set

The data structure file in the 2008 brain-computer interface competition data set Data sets 2a also emphasizes the starting point of each start of imagination. Every time the motor imagery time reaches 4 seconds, the data is intercepted. And because the motor imagery of each action needs to be performed 12 times, and a total of 6 sets of experiments are performed, the motor imagery of a single action needs to be performed 72 times, that is, the total number of motor imagery is 228 times. And because the total number of sampling points is: sampling rate (250 Hz) x duration of a single image (4s), the final result is 1000 total sampling points. Therefore, the final data type intercepted by each channel is a 228x1000 matrix.

According to the "A Step-by-Step Tutorial for a Motor Imagery-Based BCI" paper published by Hohyun Cho and Minkyu Ahn in 2018, the data results obtained in the two EEG channels C3 and C4 in 25 EEG channels It is shown that the two EEG channels C3 and C4 have the most obvious characteristics change in the motor imagery of the left and right hands. But when we discuss the four types of movement (tongue, foot, left hand, right hand), we need to discuss the new EEG channel, which involves the tongue, foot, left hand, and right hand C3, C4, Cz, Fz, and Pz. EEG channel performs feature extraction and classification.

## 3.2. Common spatial pattern (CSP)

The CSP algorithm is a very successful and frequently used approach in the EEG-based MI BCI application sector. Used to extract and identify characteristics from brain signals from two conditions—usually left/right hand MI.(Lemm *et al.*, 2011). In this article, we first used the CSP algorithm to classify the left-handed and right-handed EEG data. CSP is a feature extraction method that uses the spatial distribution of features to project multi-lead EEG signals from two types into subspaces and decompose them into different spatial patterns(Ahn and Chan Jun, 2018). The basic principle: use the diagonalization of the matrix to find a set of optimal spatial filters for projection, to maximize the variance of the two types of signals, to obtain an eigenvector with a higher degree of discrimination. Vectors are a popular spatial filter that concentrates on channels that are particularly good at differentiating between the two classes. The following optimization issue exemplifies this:

$$\max_{w}\left(\frac{w^T C_1 w}{w^T C_2 w}\right), \tag{1.1}$$

Where T denotes transposition, Ci is the spatial covariance matrix of Xi in the i-th type, and Xi denotes the i-th type's original data (a matrix of size # channel number # time samples), assuming that the EEG signal's mean value is zero. This assumption is generally met when the EEG signal is band-pass filtered. This is how the optimization issue looks like:

$$C_1 w = \lambda C_2 w. \tag{1.2}$$

This develops into a generalized eigenvalue issue. We can find the filter or eigenvector, that corresponds to the greatest eigenvalue by solving this issue. The feature vector W spatial filter and (W-1) T spatial mode are referred to. We may call the filter W a de-mixing matrix and (W-1) T a time-point mixing matrix at the same time. If X represents the observed data (mixed data), then Z (=WTX) represents the projected data (demixed data or source data). As a result, X (=(W1) TZ) is the combined data from many sources in Z. The spatial filter's value reveals which channels are crucial for retrieving source characteristics. And the values in the spatial model explain which sources are important in generating mixed data X。 The EEG signal is projected onto the w filter when using CSP for feature extraction. The logarithm of the variance of the projected EEG signal is then calculated.

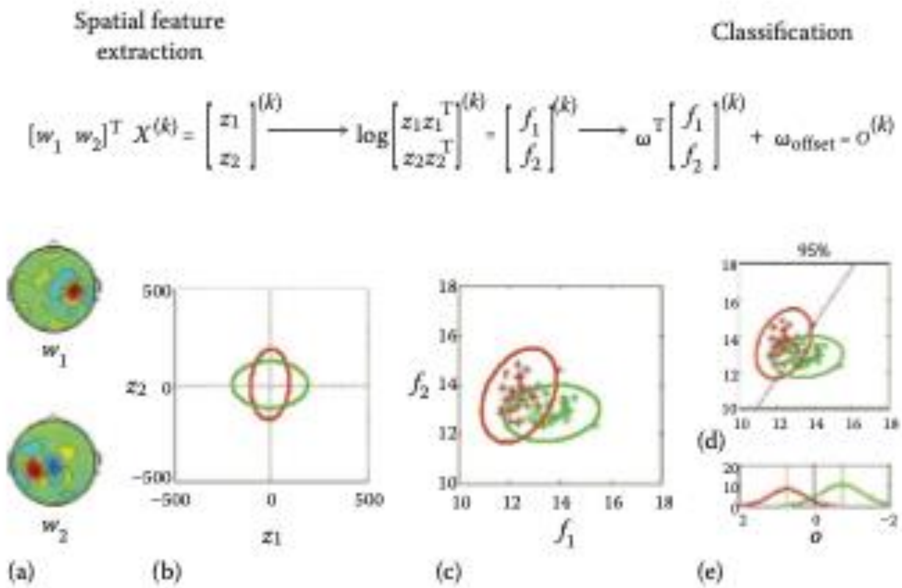


Figure7. Conventional CSP and FLDA model: (a) CSP filters; (b) projected signal variance: green indicates left-hand MI and red indicates right-hand MI; (c) log variance of projected feature; (d) FLDA’s dis- crimination line; and (e) distributions of classifier outputs for two classes.(Cho *et al.*, 2015)

### 3.2.1. Research on Feature Extraction Based on CSP Algorithm

As a feature extraction method of EEG signals, the spatial filtering method has many possibilities of realization. Spatial filtering can be briefly summarized as reducing the effect of a spatial blur, because the distance between the sensor or lead and the signal source and the uneven tissue between them may produce spatial blur. Therefore, it is necessary to try different methods to reduce the spatial blur and improve the fidelity of the signal. This is also the original intention of the spatial filter.

### 3.2.2. CSP algorithm flow for two classes of the EEG data

The basic theory of the Common Spatial Pattern (CSP) algorithm is: suppose that $x_A$ and $X_B$ are the EEG signals under two different types of motor imaging modes, the dimension is N×T, (for a single experimental task), where N represents the number of channels for signal acquisition, T represents the data length of each channel, and T>N. If the noise of the signal is ignored, the original EEG signal can be represented by a mixture of multiple signals, the mixing matrix is as follows：

$$X_A = [C_A \quad C_C]\begin{bmatrix} S_A \\ S_C \end{bmatrix}, X_B = [C_B \quad C_C]\begin{bmatrix} S_B \\ S_C \end{bmatrix} \tag{1.3}$$

In the formula, $C_A$ contains $m_a$ airspace patterns related only to $X_A$, and $C_B$ contains $m_a$ airspace patterns related only to $X_A$.

$C_C$ also contains $m_c$ airspace modes related to $X_A$ and $X_B$. The basic principle of the general airspace model algorithm is to use the difference between $X_A$ and $X_B$ data to estimate $C_AS_B$ and $C_BS_B$.

The general spatial model algorithm first calculates the normalized covariance matrix $R_A$ and $R_B$ of $X_A$ and $X_B$

$$R_A = \frac{X_A X_A^T}{trace(X_A X_A^T)}, R_B = \frac{X_B X_B^T}{trace(X_B X_B^T)} \quad (1.4)$$

In the above formula, $X^T$ represents the transposition of X, and trace(X) represents the trace of X, that is, the sum of the elements on the diagonal of X. Average the spatial covariance matrices obtained from multiple experiments to obtain the average covariance matrices $R_A$ and $R_B$. Then the mixed covariance matrix R is:

$$R = \overline{R_A} + \overline{R_B} \quad (1.5)$$

Then perform an eigenvalue decomposition on the mixed covariance matrix R to get

$$R = U_0 \sum U_0^T \quad (1.6)$$

In the above formula, $U_o$ is the eigenvector of the mixed covariance matrix R, and $\Sigma U_0^T$ is a diagonal matrix composed of the eigenvalues corresponding to the eigenvector of R.

Construct a whitening matrix P：

$$P = \sum^{-1/2} U_0^T \quad (1.7)$$

Then $R_A$ and $R_B$ can be whitened into

$$S_A = P\overline{R_A}P^T, S_B = P\overline{R_B}P^T \quad (1.8)$$

And $S_A$ and $S_B$ have the following two properties

(1) $S_A$ and $S_B$ have a common feature vector:

$$S_A = U\sum{}_A U^T, S_B = U\sum{}_B U^T \tag{1.9}$$

(2) (2) The sum of eigenvalues corresponding to $S_A$ and $S_B$ is always 1, that is：

$$\sum{}_A + \sum{}_B = I \tag{1.10}$$

This means that for the same eigenvector, the largest eigenvalue in $S_A$ will make $S_B$ correspond to a small eigenvalue; conversely, the largest eigenvalue in $S_B$ will make $S_A$ correspond to the smallest eigenvalue. If the eigenvalues in $S_A$ are arranged in descending order and the eigenvectors are adjusted accordingly, the corresponding eigenvalues in $S_B$ can be arranged in ascending order. Assuming that $X_A$ and $X_B$ strictly satisfy the model of formula (3.17), the form of $\sum_A$ and $\sum_B$ is as follows:

$$\sum{}_A = \begin{pmatrix} \overbrace{\begin{matrix} 1 & & \\ & \ddots & \\ & & 1 \end{matrix}}^{m_a} & & 0 \\ & \overbrace{\begin{matrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_{mc} \end{matrix}}^{m_c} & \\ 0 & & \overbrace{\begin{matrix} 0 & & \\ & \ddots & \\ & & 0 \end{matrix}}^{m_b} \end{pmatrix} \tag{1.11}$$

$$\Sigma_B = \begin{pmatrix} \overbrace{\begin{matrix} 0 & & \\ & \ddots & \\ & & 0 \end{matrix}}^{m_a} & & 0 \\ & \overbrace{\begin{matrix} \delta_1 & & \\ & \ddots & \\ & & \delta_{mc} \end{matrix}}^{m_c} & \\ 0 & & \overbrace{\begin{matrix} 1 & & \\ & \ddots & \\ & & 1 \end{matrix}}^{m_b} \end{pmatrix} \tag{1.12}$$

First, $\Sigma_A$ and $\Sigma_B$ are sorted. Based on the difference between the first $m_b$ and last $m_b$ feature values, the data can be classified into two types. Based this principle, a common spatial domain projection matrix can be designed:

$$SF = U^T P \tag{1.13}$$

If the first $m_a$ rows and the last $m_b$ rows of the eigenvector U arranged in the order of eigenvalue size are selected to form a new eigenvector U, a simplified co-space projection matrix is obtained:

$$SF' = U'^T P \tag{1.14}$$

$X_A$ and $X_B$ can be decomposed into:

$$Z_A = SF' \cdot A \tag{1.15}$$

$$Z_B = SF' \cdot X_B \tag{1.16}$$

The covariance matrix of $Z_A$ is calculated as:

$$R_{Z^a} = Z_a Z_a^{\ T} = SF' \cdot X_A (SF' \cdot X_A)^T = U'^T P X_A X_A^T P U' = U'^T S_a U' = \sum_a' \tag{1.17}$$

Among them, $\sum_a'$ is the first $m_a$ and last $m_b$ lines of $\sum_a$

Similarly, the covariance matrix of $Z_B$ can be obtained as:

$$R_{Zb} = \sum_b' \tag{1.18}$$

Based on the difference between $\sum_a$ and $\sum_b$, the covariance matrices of $Z_A$ and $Z_B$ after $X_A$ and $X_B$ are projected transformation can be used as feature vectors for classification learning. The normalized feature vector of the two types of data can be expressed as:

$$f_{A,i} = \frac{R_{Za,i}}{\sum_{i=1}^{m_a+m_b} R_{Z_a,i}} \tag{1.19}$$

$$f_{B,i} = \frac{R_{Z_b,i}}{\sum_{i=1}^{m_a+m_b} R_{Z_b,i}} \tag{1.20}$$

Then the feature vectors of the two types of data A and B are:

$$\begin{cases} f_A = [f_{A,1}, f_{A,2}, \cdots f_{A,m_a+m_b}]^T \\ f_B = [f_{B,1}, f_{B,2}, \cdots f_{B,m_a+m_b}]^T \end{cases} \tag{1.21}$$

## 3.3. CSP Feature Extraction for four classes of the EEG data

For numerous years, the CSP algorithm has been widely utilized in the feature extraction of EEG data based on event-related synchronization/desynchronization, which was initially one of the approaches used to diagnose aberrant EEG. CSP is also a supervised linear dimensionality reduction approach that can discover a set of directions in space that are ordered by the energy difference between the two classes of signals and then project the original signal in these directions. This article may be drawn that the process of CSP processing the two Classes of original signals is based on the derivation of the feature vectors of the two Classes of data in the previous section.

It may be described as a search for a spatial filter that allows the two Classes of signals to be differentiated to the maximum degree possible after they have been spatially filtered. The technique works by diagonalizing two covariance matrices at the same time so that one class of signal has the most variance and the other has the least. In addition, there are four classes of EEG signals in this topic: left hand, right hand, feet, and tongue. The four categories of issues may be converted into two classes of problems for feature extraction using the following two methods:

### 3.3.1. Pair-Wise CSP(PW-CSP)

The feature extraction of four classes of EEG signals, which correspond to the movement imagination of the left hand, right hand, feet, and tongue, is the challenge to be tackled in this article. Using the "Pair-Wise" CSP technique for feature extraction necessitates feature extraction on two of the four categories of issues at a time, transforming the four classes of problems into six two classes. The approach generates six spatial filters in total. The signal is delivered to the classifier after passing through six spatial filters to create 12 feature vectors.

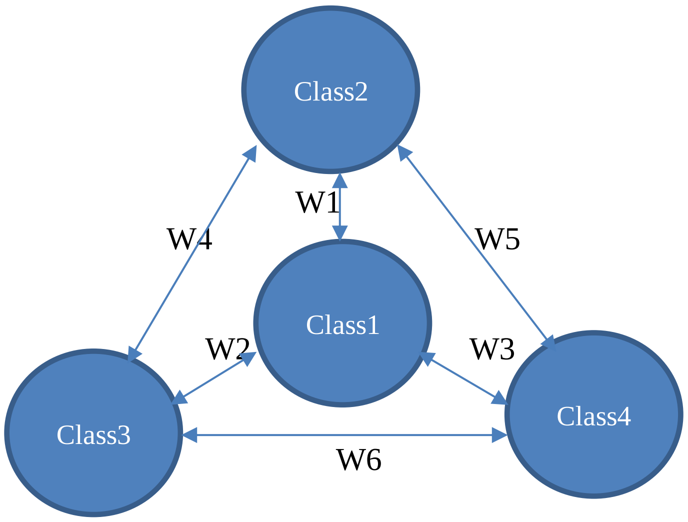


Figure8: The diagram of solving the four classess problem by PW-CSP

In the figure, class 1, class 2, class 3, and class 4 can represent the left hand, right hand, feet, and tongue respectively.

For the four classes of motor imagery problems, W1 to W6 represent the spatial filter constructed between every two categories. So far, this article can extract the features of the four classes of samples sets according to the steps of CSP for feature extraction of the two classes of sample sets.

### 3.3.2. One-Versus-Rest CSP (OVR-CSP)

Different from PW-CSP, "One-Versus-Rest" CSP regards one of the four classes as one class of problems, and the other three classes as one class of problems. Therefore, a total of four classes of problems have been transformed into Four binary classification problems. Adopting this kind of scheme needs to construct 4 spatial filters. The signal passes through 4 filters to get 8.

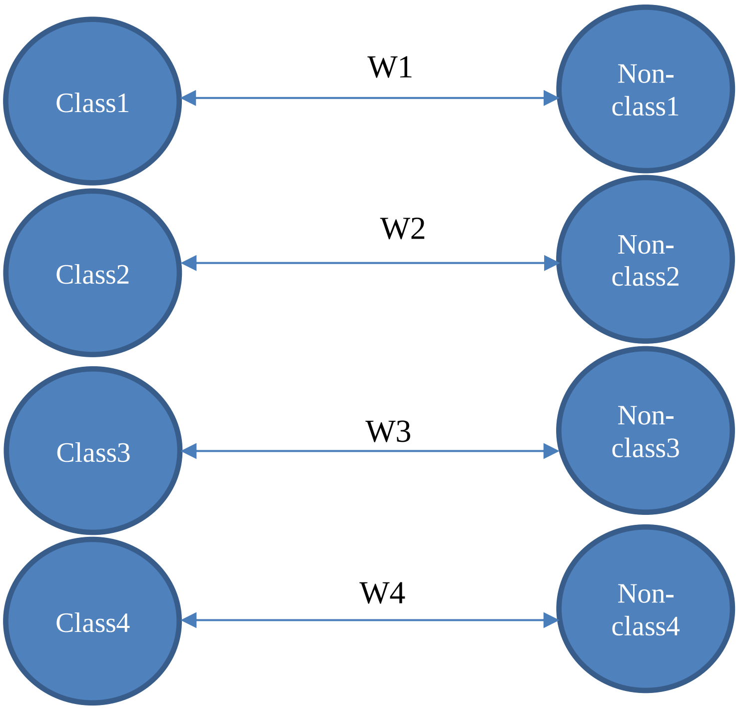


Figure9: The diagram of solving the four classess problem by OVR-CSP

In the figure, class 1, class 2, class3, and class 4 can represent the left hand, right hand, foot, and tongue, respectively.

For the four classes of motor imagery problems, W1-W4 represents the spatial filter constructed between each of the two categories. So far, this article can perform feature extraction on four classes of samples sets according to the steps of CSP for feature extraction of two classes of sample sets.

# Chapter 4 - Result

This chapter is divided into 4 parts. The contents of the first three sections respectively show the Classification of two classes of motor imagery using CSP features, Classification of four classes of motor imagery using OVR-CSP features, and Classification of four classes of motor imagery using PW -CSP features Nine sets of different EEG data ('A01E','A02E','A03E','A04E','A05E','A06E','A07E','A08E','A09E’) finally obtained under these three-classification methods accuracy result. The content of the last section is: (1) Compare the maximum, minimum, and average values of the data obtained under the three different classification algorithms in the first three sections (2) Calculate the values of Standard Deviation, maximum Kappa and A paired t-test under the OVR-CSP and PW-CSP algorithms respectively, and discuss, analyze, and compare them. (3) Summarize what is the status of different numerical responses under the three methods. And find out which algorithm works better when classifying 4-class data

## 4.1. Classification of two classes of motor imagery using CSP features

| Subject | 'A01E' | 'A02E' | 'A03E' | A04E' | 'A05E' | 'A06E' | 'A07E' | 'A08E' | 'A09E' |
|---|---|---|---|---|---|---|---|---|---|
| accuracy | 0.7986 | 0.7986 | 0.7986 | 0.7986 | 0.7986 | 0.7986 | 0.7986 | 0.7986 | 0.7986 |

Table1: The result of using CSP features to classify two classes of motor imagery

Use the CSP algorithm to classify the 9 subjects of EEG data given('A01E','A02E','A03E','A04E','A05E','A06E','A07E','A08E','A09E’), Finally, we can find that 4 features are generated in the work area of MATLAB. At this time, because we have 2 classes（Because the CSP algorithm can only handle two classification problems）. So the chance level is 50%. So the normal accuracy should be 50%, we can see in table 1, When using the CSP method classifies data, The accuracy of all data generated is the same, and far exceeds the normal accuracy.

## 4.2. Classification of four classes of motor imagery using OVR-CSP features

| Subject | 'A01E' | 'A02E' | 'A03E' | A04E' | 'A05E' | 'A06E' | 'A07E' | 'A08E' | 'A09E' |
|---|---|---|---|---|---|---|---|---|---|
| accuracy | 0.42 | 0.236 | 0.5868 | 0.2847 | 0.2882 | 0.3576 | 0.4826 | 0.3715 | 0.434 |

Table 2: The result of using OVR-CSP features to classify the four classes of motor imagery

Use the OVR-CSP algorithm to classify the 9 subjects of EEG data given('A01E','A02E','A03E','A04E','A05E','A06E','A07E','A08E','A09E’), Finally, we can find that 16 features are generated in the work area of MATLAB. At this time, because we have four classes. So the chance level is 25%. So the normal accuracy should be 25%, we can see in table 2, When using the OVR-CSP method classifies data, subject3 has the best accuracy, reaching 58.68%, and subjects1, 7, and 9 also have higher accuracy of 42%; 48.26%; 43.4%, respectively. But we can find that subject2 has the lowest accuracy when using the OVR-CSP method, which is only 23.6%.

## 4.3. Classification of four classes of motor imagery using PW-CSP features

| Subject | 'A01E' | 'A02E' | 'A03E' | A04E' | 'A05E' | 'A06E' | 'A07E' | 'A08E' | 'A09E' |
|---|---|---|---|---|---|---|---|---|---|
| accuracy | 0.3021 | 0.2604 | 0.4688 | 0.2986 | 0.2778 | 0.3264 | 0.4479 | 0.4375 | 0.4479 |

Table 3: The result of using PW-CSP features to classify the four classes of motor imagery

Use the PW-CSP algorithm to classify the 9 subjects of EEG data given('A01E','A02E','A03E','A04E','A05E','A06E','A07E','A08E','A09E’), Finally, we can find that 24 features are generated in the work area of MATLAB. At this time, because we have four classes. So the chance level is 25%. So the normal accuracy should be 25%, we can see in table 3, When useing the PW-CSP method classifies data, subject3 also has the best accuracy, reaching 46.88%, and subjects7, 8, and 9 also have higher accuracy of 44.79%; 43.75%; 44.79%, respectively. But we can find that subject2 has the lowest accuracy when using the PW-CSP method, which is only 26.04%.

## 4.4. Comparisions and discussion

| | OVR-CSP | PW-CSP |
|---|---|---|
| 'A01E' | 0.42 | 0.3021 |
| 'A02E' | 0.236 | 0.2604 |
| 'A03E' | 0.5868 | 0.4688 |
| 'A04E' | 0.2847 | 0.2986 |
| 'A05E' | 0.2882 | 0.2778 |
| 'A06E' | 0.3576 | 0.3264 |
| 'A07E' | 0.4826 | 0.4479 |
| 'A08E' | 0.3715 | 0.4375 |
| 'A09E' | 0.434 | 0.4479 |
| Maximum | 0.5868 | 0.4688 |
| Average | 0.3846 | 0.363 |
| Standard Deviation | 0.1098 | 0.0853 |

Table 4: The result of using PW-CSP and OVR-CSP features to classify the four classes of motor imagery, And the maximum value, average value, and Standard Deviation of the results obtained under these two classification algorithms.

The results showed that the OVR extension to CSP yielded the best-averaged mean kappa value (0.3846). A paired t-test revealed there was no statistically significant difference between the OVR and PW approaches ($p = 0.3312$), We can see that the average kappa value generated when using the OVR-CSP method to classify data is better. It performs well in the 4 subjects (subject1, subject3, subject7, and subject9), especially in subject3 the medium accuracy reached the highest 58.68% and the average kappa value is 38.46%. When using the PW-CSP method to classify data, it performs well in 4 subjects (subject3, subject7, subject8, and subject9), but its average kappa value only reaches 36.3%. when comparing the two methods of OVR-CSP and

PW-CSP, the calculation cost of the OVR-CSP method will be lower because it only uses 4 classifiers (w1, w2, w3, w4) in the classification process. ), but PW-CSP uses 6 classifiers (w1, w2, w3, w4, w5, w6,) in the classification process. From the perspective of Standard Deviation, the Standard Deviation of OVR-CSP is larger, which means that the difference between most of its values and its average value is greater. When using the OVR-CSP method to classify data, the degree of dispersion between the 9 sets of data is relatively large. The Standard Deviation of PW-CSP is relatively smaller, and a smaller standard deviation means that these values are closer to the average. When using the PW-CSP method to classify the data, the degree of dispersion between the 9 sets of data is relatively small.

# Chapter 5 - Conclusion

## 5.1. Evaluation

This project is dedicated to the development of new smart wheelchairs. Compared with traditional smart wheelchairs, this project is committed to combining MI BCI technology with wheelchairs and realizing the multi-party free movement of wheelchairs.

Currently, MI BCI is mainly applied to 2 classes. To control the smart wheelchair, 4 commands are needed, forward, stop, turn left, and right, so a multi-class MI-BCI is needed. So this project proposed The two algorithms of CSP and PW-CSP deal with the problem of four classifications. Compared with the three classification methods mentioned in the article, the CSP algorithm is only for the problem of two classifications. The accuracy of each group obtained by its classification is the same, and the average accuracy is 79.86%, But OVR-CSP and PW-CSP are extended based on the CSP algorithm, which can classify 4 classes. The average accuracy of 4 classifications for the same nine sets of data is 38.46% and 36.3%, respectively. To obtain the optimal algorithm, we compared the results obtained by OVR-CSP and PW-CSP when the same 9 sets of data were processed in 4 classifications (kappa average, maximum, Standard Deviation, and the paired t test.). By comparing the average values of kappa, the average values of kappa of OVR-CSP and PW-CSP are relatively close, being 38.46% and 36.3%, respectively. Therefore, the optimal algorithm cannot be compared based on the average value alone. In comparison, the OVR-CSP algorithm produced a more prominent maximum accuracy when classifying the third set of data, which was 58.68%. The maximum accuracy of the PW-CSP algorithm is only 46.88%. In terms of Standard Deviation, OVR-CSP has a higher Standard Deviation, implying that the gap between the majority of its values and the average value is larger. That is, the degree of dispersion across the 9 sets of data is rather significant when utilizing the OVR-CSP technique to categorize data. PW-CSP has a lower standard deviation, which indicates that these values are closer to the average. That is, the degree of dispersion across the 9 sets of data is quite minimal when utilizing the PW-CSP technique to categorize the data. when comparing the two methods of OVR-CSP and PW-CSP, the calculation cost of the

OVR-CSP method will be lower because it only uses 4 classifiers (w1, w2, w3, w4) in the classification process, but PW-CSP uses 6 classifiers (w1, w2, w3, w4, w5, w6,) in the classification process. A paired t-test revealed no significant difference between the OVR and PW approaches ($p = 0.3312$),

After comparing the two algorithms in many aspects, we can see that the difference between the two methods is not very big. The average accuracy obtained is closer. Therefore, in this project, we think that using the OVR-CSP algorithm for 4 classes classification for the same 9 sets of data is like the results obtained by using the PW-CSP algorithm for 4 classes classification. It also proves that there is no obvious difference between the OVR-CSP and PW-CSP algorithms in data classification capabilities.

## 5.2. Future Work

In the process of performing the two algorithms, The OVR-CSP algorithm generates 16 features and the PW-CSP algorithm generates 24 features. Given the small training size, these big numbers of features would lead to deteriorated classification results due to overfitting. Thus, in the future, a feature selection algorithm can be added to improve the classification accuracy by selecting more discriminative features in the future, other classification methods can be used to perform multi-class MI-BCI classification on EEG data. For example, use the Filter Bank Common Spatial Pattern (FBCSP) algorithm classification method to classify EEG data and select features. For EEG data, FBCSP incorporates four steps of signal processing and machine learning: a filter bank with multiple Chebyshev II bandpass filters, spatial filtering using the CSP method, CSP feature selection, and classification of selected CSP features. Based on the training data tagged with the relevant motor imagery, the CSP projection matrix, discriminative CSP features, and classifier model of each filter band are constructed. In the assessment phase, these characteristics from the training phase are utilized to compute a single trial motor imagining action. And based on the FBCSP algorithm, OVR-FBCSP, PW-FBCSP, and DC-FBCSP can be extended(Ang *et al.*, 2012). The final results of these classification algorithms are compared with the results of OVR-CSP and PW-CSP obtained in this article, and the optimal classification algorithm is obtained. Even if there is ample time, you can consider starting from the data set. Consistent with what is said in the article, the EEG data is collected and processed in the laboratory. The collected data is classified and feature selected, and the final data obtained is imported into the designed physical wheelchair. Verify that the wheelchair can work normally, what are the external interference factors, and the reaction time and accuracy of the wheelchair in operation can be obtained. In future experiments, the SVM classifier method can also be used to classify the four classes of motion calculation data. The support vector machine is simply a two-class classifier; it can only tackle two sorts of issues, and if the training sample set is too huge or excessively imbalanced, the training and classification effects will be severely harmed. The two types of SVM multi-value classifier constructions that are widely employed are as follows: （1）One-Against-The-Rest；（2）One-Against-One;

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