# Abstract

In the age of technology, where people have tried to minimise the works done by humans and shift it to robots or machines, drone has gained significant importance. Drone is widely used for its flexibility, user-friendliness, and easy interface. There are many options available to control a drone, from using a remote control to using thoughts or mental commands. In using mental commands, a user is asked to think of one four-directional movements which are left, right, push, and pull and the drone will move accordingly.

In this project, we focus on controlling the drone by using mental commands. Non-invasive Brain Computer Interface is used to extract the motor imaginary tasks from the user. The tools used in this experiment are Emotiv EPOC (14-channel headset), Emotiv Control Panel, and Emotiv Test Bench to extract the EEG signals. In the framework used throughout this experiment, we comprise Common Spatial Pattern (CSP) and Meta-Cognitive Interval Type-2 Fuzzy Inference System Classifier (McIT2FIS) algorithms. The CSP is used to extract features from the EEG signals while McIT2FIS is used to classify the features into left, right, push, and pull commands.

CSP has been widely used to extract features from EEG signals. However, CSP has a feature that arguably is considered as a shortcoming: it was proposed only for two-class paradigms. In this project, we explore pair-wise method to extend CSP to four-class paradigms.

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# Introduction

## Background on Common Spatial Pattern

It is impossible to differentiate directly which EEG data represents one class or the other. We need to deploy an efficient algorithm to do this task. One algorithm that is very widely used and deployed to serve this purpose is Common Spatial Pattern (CSP) algorithm.

CSP is mathematical procedure that separates EEG data into two different additive subcomponents which have maximum differences in variance between two windows [1]. Given EEG data of two different classes, CSP computes spatial filters that maximise the ration of the variance of the data conditioned on one class and the variance of the data conditioned on the other class [2].

This feature of CSP, however, arguably is considered as a shortcoming as it is incapable of differentiating multi-class EEG data. Many researches have been done on the extensions of CSP to multi-class paradigms. While many are largely based on heuristics, one research has been done to extend CSP to multi-class paradigms based on joint approximate diagonalization (JAD) of several EEG covariance matrices conditioned on class labels that has been shown to perform well in practice [2].

In this project, we focus less on modifying the mathematical procedure and more on utilising and applying the existing procedure on pair-wise approach.

## Background on Meta-Cognitive Inference Meta-Cognitive Interval Type-2 Fuzzy Inference System Classifier (McIT2FIS)

## Background on Pair-Wise (PW) Classification Approach

Given that *c*, *c’*∈ {1,2,3,4} represents the left, right, push, and pull motor imagery, Pair-Wise approach computes the features that discriminates every pair of classes with one class of which the classifier had already had the knowledge used as a benchmark. For example, for the PW classifier where *c* = 1 is the known class and *c’* = 2, 3, or 4; each one of the classes in *c’* is discriminated from class 1 using CSP for each discrimination.

This Pair-Wise method has previously been explored as an extension to Filter Bank Common Spatial Pattern that employed the Naïve Bayesian Parzen Window (NBPW) classifier [3].

# Literature Review and Previous Work

In this chapter, the research that is relevant to this project is discussed.

## Common Spatial Pattern

For the analysis, the raw EEG data of a single trial is represented as matrix *E,* where *N* is the number of channels (recording electrodes) and *T* is the number of samples per channel. The normalised spatial covariance of the EEG can be obtained from

(1)

where ‘ denotes the transpose operator and trace() is the sum of the diagonal elements of . The spatial covariance of the motor imagery class, 1 or 2 is achieved by calculating the average of all samples in each class. Then, the composite covariance c is denoted as

c 1 2

(2)

The composite covariance c is furthered factored into

c ccc’

(3)

where c refers to the matrix of eigenvectors and c is the matrix of eigenvalues. The eigenvalues are assumed to be sorted in descending order.

The whitening transformation is represented by

(4)

This transformation equalises the variances in the space spanned by c, i.e.,all eigenvalues of are equal to one. If 1 and 2 are transformed as

1 and 2

(5)

then and share common eigenvectors, i.e., if

1 then 2 and

(6)

where is the identity matrix. Since always equals to 1, the largest eigenvalue for has the smallest eigenvalue for and vice versa.

With the projection matrix , the decomposition of a trial is given as

(7)

The columns of are the common spatial patterns.

In this project, the first and last 3 rows of Z in the transformed signals, Z’ are employed for feature extraction. The log-variance features is derived as

(8)

where is a m-dimensional feature vector. The calculations as shown in equations (7) and (8) were repeated for each sample to derive the log-variance features [4].

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