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Research paper

Single channel electroencephalogram (EEG) brain computer interface (BCI) feature extraction and quantization method for support vector machine classification

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Abstract

Over the recent years, there has been a huge interest towards Electroencephalogram (EEG) based brain computer interface (BCI) system. BCI system enables the extraction of meaningful information directly from the human brain via suitable signal processing and machine learning method and thus, many researches have applied this technology towards rehabilitation and assistive robotics. Such application is important towards improving the lives of people with motor diseases such as Amytrophic Lateral Scelorosis (ALS) disease or people with quadriplegia/tetraplegia. This paper introduces features extraction method based on the Fast Fourier Transform (FFT) with logarithmic bin-ning for rapid classification using Support Vector Machine (SVM) algorithm, with an application towards a BCI system with a shared con-trol scheme. In general, subjects wearing a single channel EEG electrode located at F8 (10-20 international standards) were required to syn-chronously imagine a star rotating and mind relaxation at specific time and direction. The imagination of a star would trigger a mobile robot suggesting that there exists a target object at certain direction. Based on the proposed algorithm, we showed that our algorithm can distin-guish between mind relaxation and mental star rotation with up to 80% accuracy from the single channel EEG signals.

Keywords: *Brain Computer Interface (BCI); Electroencephalogram (EEG); Mobile Robot; Support Vector Machine (SVM).*

1. Introduction

Recently, Brain Computer Interface (BCI) has been a huge topic of interest among researchers in medical, rehabilitation, healthcare, robotics and even entertainment field. This is because Electroencephalogram (EEG) based BCI system enables machine to directly obtain information from the brain, bypassing indirect means such as using limbs to issue commands to a computer. By accurately classifying features from EEG recording, one can exploit its use towards developing assistive and rehabilitative robotic system for healthcare purposes. Many studies have successfully demonstrated the feasibility of EEG-based BCI towards such application. This includes using BCI towards controlling a robotic wheelchair system for Amytrophic Lateral Scelorosis (ALS) patient [1] , control of telepresence robot for people with severe motor disabilities [2], as well as exoskeletal robotic system paraplegic patient [3].

Despite its applicability towards rehabilitation, assistive and healthcare robotics, the use of EEG-based BCI for this application is still a long way from being available in the general consumer market. Most researches use the conventional multi-channel electrodes for EEG recording. While the use of multiple channel electrodes is providing more insight towards user's brain activity, it lacks ergonomic considerations, high cost and impractical for typical daily usage.

Therefore, to address the aforementioned issue, few researches have ventured towards developing BCI system that uses single channel electrode for robotic purposes. One typical work is by Hazim et. al [4], in which probability density function (PSD) was used to classify spectral features between mental task for controlling a mobile robot and Tarmizi et. Al in which [5] spectral features from single channel EEG electrode was classified using Artificial Neural Network (ANN) to determine the subject's intention in controlling an electrical wheelchair.

In most studies concerning BCI, spectral features obtained using FFT algorithm is divided into sub-band frequency: Delta <4 Hz, Theta 4-7 Hz, Alpha 8-13 Hz, Beta 13-30 Hz, Gamma >30 Hz and Mu 8-12 Hz [5] . These sub-bands frequencies are often related to certain physiological and cognitive states. For example, a decrease of power in Mu frequency band in the motor cortex, is associated with the subject performing motor imagery (MI) tasks [6], while increase in alpha and theta power in frontal scalp region indicates subject's mental relaxation period [7], [8]. Respectively, this serves as the basis for either motor imagery-based BCI or mental-based BCI for robotic control purposes.

This paper introduces a new approach of quantizing spectral features of single channel EEG for mental-based BCI by using the concept of logarithmic binning and investigate its effect to Support Vector Machine (SVM) classifier accuracies. SVM is chosen as classifier as it is highly suitable for binary classification problem and is widely used classification technique for EEG based BCI system [9]. Differ than conventional approach that solely focuses on sub-band frequencies below 40 Hz, proposed approach exploits the use of the entire spectral frequencies of EEG signal not limited to the aforementioned sub-band frequencies. This allows BCI designer to produce feature vectors of different sizes by setting an appropriate number of bins. Such flexibility allows system designer to choose between computational complexity and accuracy and is important in designing practical BCI system for general consumer market.

2. Methodology

2.1. Experimental setup

This section presents the experimental setup for the system. This experiment uses a single EEG signals of 10- 20 international standard location (F8). The reference potential position was placed at the right ear lobe. An EEG paste was used to increase the electrode conductivity. The channel was directly connected into BMA-400 EEG-amplifier which provides specific gain constant for bio signal amplification. The EEG signal was digitized using National Instruments (NI)-PCI-6229 Data Acquisition Card (DAQ) which was connected into Peripheral Component Interconnect (PCI) slot of a personal computer's (PC) motherboard. All necessary specification of a PC in used are listed here:

- 2.50 GHz i5-2520M Intel® Core™
- Fedora 8 RTAI Linux-kernel-2.6.23-42-fc8
- COMEDI's pci-6229 device driver Control and Measurement Device Interface

COMEDI is a collection of device drivers for a variety of common data acquisition plug-in boards (e.g. NI-PCI-6229 DAQ card). The system was designed to acquire a single signal of EEG and was exploited using C language as our processing tool. The necessary setting (e.g. sampling frequency, DAQ's I/O port and acquisition mode) for data acquisition process was controlled by a set of C functions provided by COMEDllib.

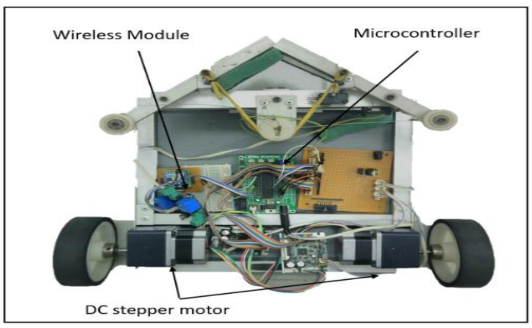
2.2. Experimental procedure

In this section, the experimental procedure for data collection is presented. 27 subjects were voluntarily participating in this experiment. There was no initial training session provided to all of them
Based on previous study by [4] two mental states were used as below:

- Mind relaxation (control condition).
- Imagine a 2-D star rotating in clockwise direction (target condition).

The subjects were required to sit on a chair comfortably and facing towards a mobile robot which was located about 2 meters from their feet as shown in Figure 1. Before the experiment took place, all subjects were given a briefing session regarding the experimental procedure for about 5 minutes. Each subject was then required to draw a 2-D star and was given 5 seconds to glare at the star.

(A)



(B)

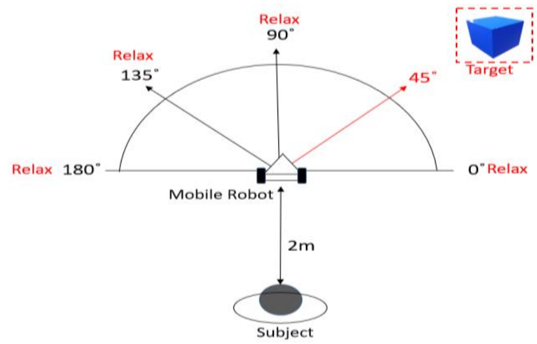


Fig. 1: Overall, Experimental Setup (A) Wireless Mobile Robot that Was Used in the Experiment (B) Illustration of the Control Scheme, A Box Is Placed at 45˚ Serve as the Target to Be Selected by Performing Mental Star Rotation.

Simple assessment was carried out after the experiment session. All subjects had no previous experience with meditation and specific mental illness record. Subjects were in a healthy condition during the experiment period.
The procedure was developed to allow 'target' selection during scanning process of a mobile robot. The control area was divided into five degree-based direction - 0°45°, 90°, 135° and 180° The robot is initialized to standby mode by facing towards 0° direction to the right. An object is placed at the direction of 45° where it serves as a target to be selected. As the robot "scans" or rotates towards particular angle, subject is required to perform mental relaxation except at 45˚ where the target is placed. Here subject is required to perform mental rotation to denote presence of a target. At each position, EEG data is recorded for analysis in the later stages, Figure 2 shows a control flow chart of synchronous process between direction, mental state and time.

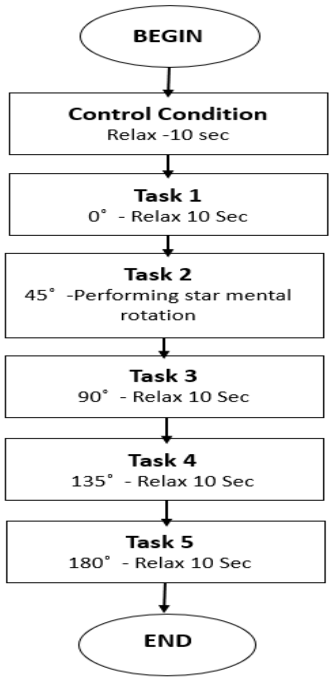


Fig. 2: Flow Chart of Control Procedure.

2.3. Parameter extraction

Similar to previous study in [7] , EEG potentials were first sampled at a sampling rate of 1024 Hz and digitized at 16-bit resolution.

Digital notch filter was then applied to remove the deterministic 50 Hz noise from power supply line. The data were the segmented into several epochs where each epoch contains 1024 data points at a time length of 1 second. To further improve classification accuracy and increase our training data, a 50% overlapping approach on the segmented epoch similar in [10] was employed. Fast Fourier Transform algorithm (FFT) was used to transform the time domain into frequency domain signal to reveal its spectral features.

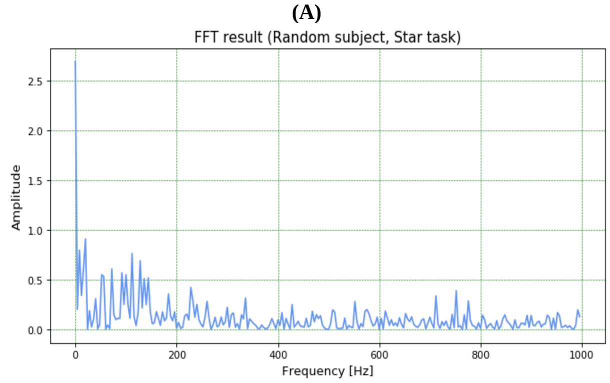
2.4. Logarithmic binning

A typical EEG signal is often associated with frequencies ranging from 1 – 40 Hz, and it is presumed that this frequency range contains most of the relevant signal. However, it is also possible that useful signal exist outside of this range as well [11]. For example, mental gestures are thought to be correlated with muscular activity, which exists outside of the 1-40 Hz range. To fully exploit the entire frequency spectrum while preserving our bias toward known source of useful signal, the concept of data binning and taking the logarithmic of power spectra was employed using the following equation:

$$P_i = 20\, log(s) \tag{1}$$

Here P_i denote logarithmic value of power spectra s which is used as the i-th bin. This offers a simple way to quantize the information contained in the full signal. For, example four contagious frequencies (1 Hz, 1.25 Hz, 1.5 Hz, 1.75 Hz) each with a spectral value of (4,4,5,5) average into a single value of 4.5. The number of bins can be adjusted to produce feature vectors of different sizes. This vector, which highlights the statistical properties of the power spectrum for each mental task, can be used as an input of variable size to the classifier. Figure 3 shows an example of feature extraction using logarithmic binning.

(A)



(B)

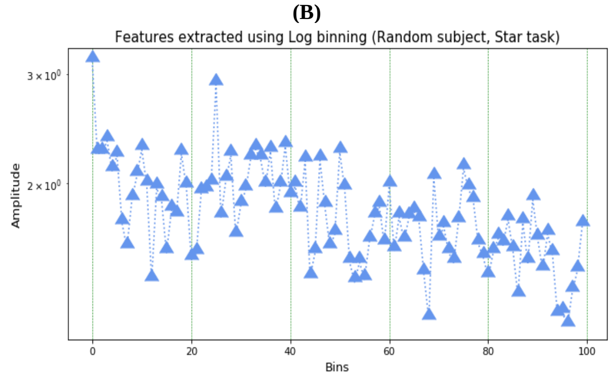


Fig. 3: Example of Feature Extraction Using Logarithmic Binning (Task 2, Star Rotation, Random Subject). (A) Spectral Feature Extraction Using FFT Algorithm. (B) Binning of A Spectral Features Using Logarithmic Binning With Numbers of Bins = 100.

2.5. Support Vector Machine (SVM) Classification

To classify the mental tasks into two classes (star rotation vs relaxation), and test the performance of the proposed quantization method, a binary classifier based on the SVM was used. In SVM, given that training vectors $x_i \subseteq \mathbb{R}^p, i = 1,2,3..n$ can belongs in either of the two classes $y \subseteq \{1, -1\}$, we aim to solve the following problem:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + c \sum_{i=1}^{n} \xi_i \tag{2}$$

$$subject\ to\ y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i\ \xi_i \geq 0, i = 1, \dots, n$$

Here two classes of y are mapped to star rotation and mental task respectively. All computations are performed using Support Vector Classifier (SVC) package from scikit-learn [12], a widely used python's machine learning library. Because of the non-linear nature of EEG signal, we employed Radial Basis Function (RBF) kernel trick to our SVM classifier.

3. Results and discussions

3.1. Inter subject classification accuracy

To gauge our classifier performance on individual subject, we first perform 8-fold cross validation method to train our SVM classifier and validate the accuracy. Only data from task 1 (mental relaxation at 0˚) and task [2] (mental star rotation at 90˚) were used to train our SVM classifier. Initially, the number of bins was randomly set at 90 as we are only interested on general classification accuracy between subjects. Figure 4 shows our classifier performance across all 27 subjects and Table 1 shows overall classification performance.

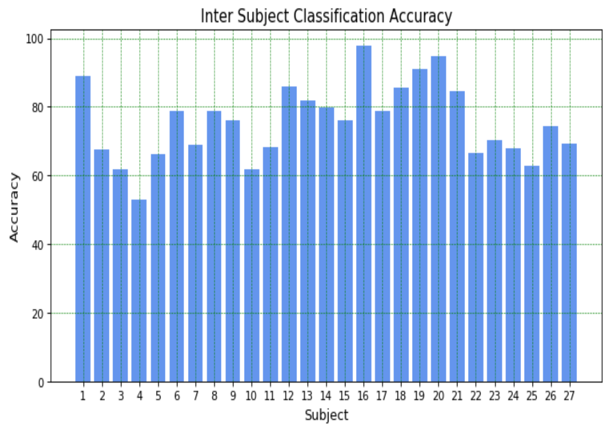


Fig. 4: Inter Subject Classification Accuracy with Number of Bins = 90.

Table 1: Inter Subject Overall Classification Performance

Maximum	Minimum	Mean
97.7 %	53.0%	75.4%

3.2. Number of bins versus classifier accuracy

As mentioned in Section 2.4, the size of feature vectors can be adjusted by varying the number of bins. We hypothesize that by increasing the number of bins to be used in our SVM classifier, performance of the classifier can be improved. In order to validate this hypothesis, the number of bins in the algorithm was iteratively increased from 0 to 250 and plotted the corresponding classifier score. Figure 5 shows the mean score (8-fold validation method) of classifier accuracy versus the number of bins. As per hypothesis, the classifier accuracy can be improved by adjusting the number of bins in our algorithm. The increase of accuracy is also evident Figure 3 (b) in which the mean score across all subject was taken and plotted against the number of bins, resulted in positive correlation with increasing number of bins.

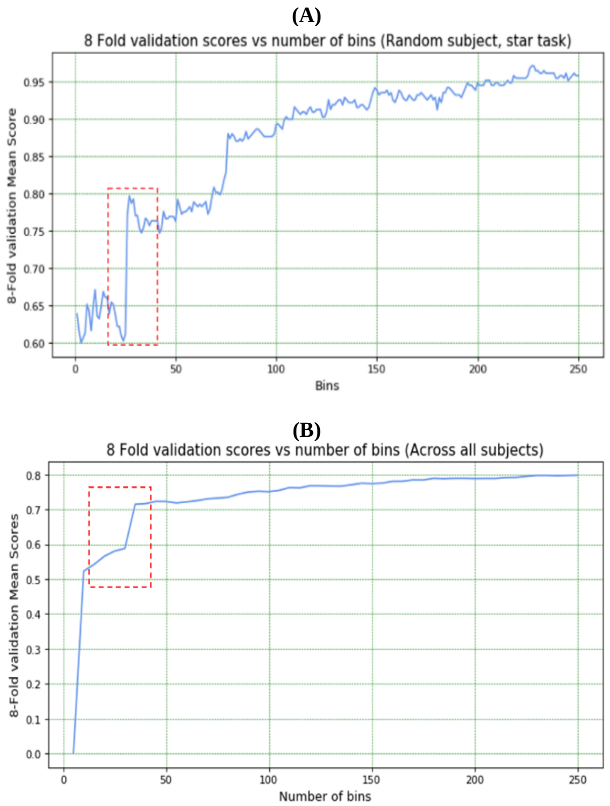


Fig. 5: Effects of Classifier Accuracy versus the Number of Bins Used. (A) Example on A Random Subject (B) Mean Score Across All 27 Subjects. Red Box Denotes Significant Increase in Accuracy at A Particular Number Of Bins.

3.3. Classifier accuracy on other mental relaxation tasks

To further test the performance of proposed algorithm, the trained SVM classifier that was used to distinguish between Task 2 and task 1, was again used to distinguish between Task 2 with Task 3 (mental relaxation at 90˚), Task 4 (mental relaxation at 135˚), and Task 5 (mental relaxation at 180˚). Based on the result shown in section 3.2, number of bins was fixed at 100 and mean score (all subjects) of our classifier accuracy at each task was calculated. The number of bins was fixed in such a way to give best trade-off between computational complexity and accuracy. Figure 6 depicts the performance of our algorithm at other mental relaxation tasks.

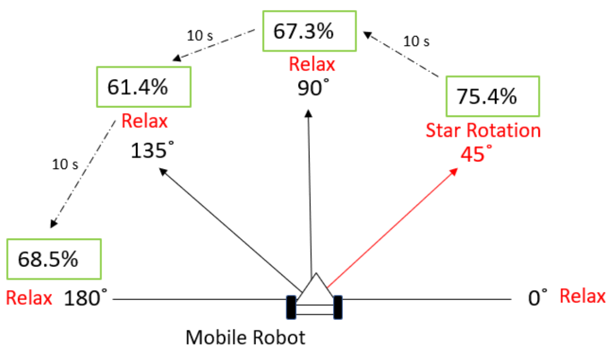


Fig. 6: Classifier Accuracy for Mental Relaxation Task at 90˚, 135˚ and 180˚.

3.4. Discussion

In general, proposed classifier shows good inter subject classification accuracy such as shown in Section 3.1. A mean accuracy of 75.4% was obtained and this indicates the algorithm managed to accurately classify most subject's mental task. From the 27 subjects, our approach manages to obtain an accuracy of more that 80% from [8] subjects, while an accuracy of below 60% was only obtained from 1 subject. This variability of classification accuracy was expected and probably was due to BCI illiteracy [13] that may have affected some of the subjects.

One differences in our approach compared to conventional mental task BCI system is that the proposed algorithm uses a selectable number of feature vectors by varying the number of bins. This approach enables BCI designer to fully utilize the entire frequency spectrum including spectrum that exist outside of 0 – 40 Hz range. Figure 5 in Section 3.2 shows that classifier accuracy correlates with the increasing number of bins. This validate earlier hypothesis that, some of the frequency that exist outside of the 0 – 40 Hz range may actually be useful in providing information that improves classification of BCI system. However, one interesting observation that can be made from this result is that the classifier's accuracy improves significantly at certain number of bins, particularly at the range of 25 -40. This can be observed at most individual classifier accuracy scores such as shown in Figure 5 (a) and is also evident on the mean classifier accuracy across all 27 subjects (Figure 5 (b)). It is also interesting to note from Figure 5(b) that usage above 40 bins will not improve the classifier score drastically with only about 0.03% increment per number of bin above this value. Classifier score of 80% is achievable when number of bins is set to near to 200 and above, but increasing the number of bins up to this value will increase computational complexity and probably impractical for real online classification purposes.

Since the ability of our system to detect target at certain location relies on the accuracy of our classifier to accurately distinguish between mental relaxation and star rotation, we test the trained classifier to distinguish mental relaxation at other position as well such as shown in Figure 6 section 3.3. We found that there is a decreased in the classifier accuracy at 90˚ robot orientation, and a further decreased at 135˚ while improving at 180˚. This observation is consistent with [7] which reported that recovery pattern for alpha wave, which is often associated with mental relaxation, was found to increase gradually over time, suggesting that alpha wave plays a dominant role in the recovery pattern during relaxation and may affect the classification accuracy. Moreover, an observation made in [14] also reported that the enhancement of alpha was observed to increase over a span of 20 seconds. This is consistent with our findings in which the classifier accuracy improves when the orientation of the robot is at 180˚, executed at around 20-30s after mental star rotation task.

4. Conclusion

This paper introduces the concept on logarithmic binning towards extracting spectral EEG features to be used with single channel BCI system that focuses on the use of mental imagery task. Our approach allows BCI system designer to fully utilize the entire frequency including range that exist above 40 Hz by adjusting the number of bins. We have shown that by increasing the number of bins, accuracy of our SVM classifier can be improved up to 80%. However, selection on the number of bins must be made with computational complexity in mind. For online classification purposes, it is best to set the number of bins just above 40, and we find 100 to give good trade-off between accuracy and computational complexity. Another factor to consider in designing mental imagery based BCI system is suppression of mental task such as rotation for relaxation requires a period of 20 s and above. Failure in doing so will result in the system unable to accurately detect user's desired intention or in our case the "target". Thus, in the future more researches needed to be carried in order to modify and improve this type of BCI.

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