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Determination of Optimal Frequency Ranges Using Common Spatial Pattern Images

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Abstract- **In this paper we present brain maps constructed for Visualization of Arrow Movement (VAM) mental tasks with EEG signals recorded from 20 locations on the scalp. Method of Common Spatial Patterns (CSP) is employed to generate the spatial maps after filtering raw EEG signals into nine different frequency bands. Separate CSPs were obtained for six subjects who participated in this study. These brain maps show distinct spatial patterns that can be used for distinguishing two mental tasks in VAM. For every subject, optimal frequency range which is useful in distinguishing mental tasks in VAM was obtained.**

Index Terms— **Common spatial patterns, Spatial filters, mental tasks, Electroencephalograph (EEG) classification.**

I. INTRODUCTION

The Electroencephalography (EEG) based Brain Computer Interface (BCI) is a noninvasive alternative communication method for people to interact with outside world or control external devices such as switches, wheelchairs, computers, or neuroprosthesis [1-4]. EEG signals which are recorded from the scalp of the user contain average electrical activities of the brain. Changes which may have occurred in the EEG signals due to various thoughts of the user are exploited in BCI. Real world applications of this technology is invaluable for patients who suffer from severe motor impairments due to incurable neurological diseases or spinal injuries. Especially this technology would be beneficial for locked in patients, as it is the only possible way for them to communicate effectively with outside world [5-7].

Most of the human thoughts do not produce detectable changes in EEG. However it is known that certain mental activities can alter EEG signals up to a level where it can be detected by signal processing methods [9]. Some of the cognitive tasks (mental tasks /thoughts) which are known to significantly alter EEG signals include, multiplication (solve non-trivial multiplications), letter composing (mentally composing a letter), visual counting (mentally visualize numbers being sequentially written on a board), imaginary hand or leg movements (imagination of hand movement or foot movement / Motor Imagery), and newly introduced set of mental tasks called visualization of arrow movements (VAM) [8,9] which consists of Imaginary Right Arrow Movement and Imaginary Down Arrow Movement. Motor Imagery (MI) mental tasks are the most heavily used and successfully implemented mental tasks in BCI [10, 11]. On the other hand VAM is a newly introduced set of mental tasks which has not been explored in detail so far.

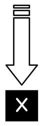
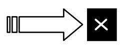
EEG waveforms of a normal subject at different mental stages often produce rhythmic patterns at characteristic frequencies between 0Hz and 80Hz. This range covers the well-known frequency bands, Delta and Theta (1 – 7Hz), Alpha (8 – 12Hz), Beta (13 – 29Hz) and Gamma (30 – 48Hz) [11, 12].

However, every mental task would not produce changes in EEG signals in all the frequency bands mentioned above. Furthermore, for a given mental task, all the subjects may not produce changes in the same band. In other words one subject may produce significant changes in one frequency band while another subject can produce changes in another band for the same mental task. This subject dependent variation in frequency bands makes it impossible to pre-determine the effective frequency bands for a given mental task. As a result, for each subject it is important to determine the frequency ranges which make the classification accuracy a maximal [13].

Knowledge of neurophysiological origin of a mental task would be helpful in identifying the source locations corresponding to the specific mental task and determining the effective EEG channels which should be employed with the mental task. In addition, this information is also valuable for recognizing and removing the potential artifacts associated with the mental task and hence substantially improves the EEG-based classification techniques. When constructing a real time BCI system, identification of effective channels and recognition of potential artifacts are the two of the most important steps required to have an effective and reliable system. One of the accurate and effective ways of obtaining information such as the best EEG channels and source locations corresponding to a given mental tasks is the use of high resolution brain maps [14-17]. Usually, brain maps are constructed either with direct imaging techniques such as fMRI and fNIRS or low cost technologies such as high density EEG. Since EEG alone cannot produce brain maps directly, various signal processing methods such as Principal Components Analysis (PCA), Common Spatial Patterns (CSP) and Independent Component Analysis (ICA) in Blind

Source Separation have been employed [17-19]. Among aforementioned imaging techniques, the CSP method has shown its efficacy in extracting topographic patterns of brain rhythm modulations for MI mental tasks. Moreover, due to relative easiness in the implementation, the majority of the brain maps for MI mental tasks are produced with CSP [14, 15, 17, 19-24]. Some research laboratories have produced high quality brain maps using common spatial filters with large number of EEG channels and identified the active areas in the cerebral cortex, effective EEG channels as well as the physiological origins associated with MI mental tasks. Moreover, brain maps corresponding to MI mental tasks along with CSP have provided information to identify biological artifacts associated with them. Based on the information gathered from memory maps produced for MI mental tasks, several research groups in USA, Germany and Austria were able to improve their real time BCI systems [14-24]. On the other hand, effective channels and physiological origins associated with other mental tasks such as newly introduced set of mental tasks VAM have not been identified so far. As a result choosing the effective EEG channels and developing effective artifact removal techniques for the above

TABLE I
MENTAL TASK LABELS AND IMAGES OF ARROWS

Mental Tasks Labels	Imagination	Image
DAM	*Imagining a down arrow hitting a square from the top*	
RAM	*Imagining a right arrow hitting a square from the left*	

mental tasks in real time BCI systems have become a challenging exercise.

As shown in Table I, VAM consists of two mental tasks;

(1) visualizing an arrow hitting a cursor from above (Down Arrow Movement - DAM)

(2) visualizing an arrow hitting a cursor from left (Right Arrow Movement - RAM)

In this paper, with the data recorded from six subjects participated in the current study, we present brain maps constructed for VAM mental task using CSP method and discuss the distinguishability of the mental tasks.

II. COMMON SPATIAL PATTERN ALGORITHMS

The method used in this paper for extraction of patterns from the EEG data is based on a method of CSP which was introduced to the field of EEG analysis by Koles [16]. However designing of optimal spatial filters of single –trial EEG using CSP method was first proposed by H. Ramose for classification of multi – channel EEG [14].

The core of the CSP method we employ in this study is based on decomposition of raw EEG signals into spatial patterns that lead to new time series whose variances are optimal in a manner that maximizes their differences for the discrimination of two EEG populations. The method used to design such spatial filters is based on the simultaneous diagonalization of two covariance matrices.

CSP method used in this study is described in detail below. Consider a single trial, an N-channel raw EEG signal S, where S is a $N \times T$ matrix and T denotes the number of samples in each channel. The normalized covariance matrix of the EEG signal can be obtained from

$$C = \frac{SS^T}{trace(SS^T)} \tag{1}$$

where ^{T} indicates the transpose operator and $trace(SS^T)$ is the sum of the diagonal elements of SS^T. Using (1) the spatial covariance matrix $\bar{C}_d \in [1,2]$ of each class C_1 and C_2, can be computed by averaging over the trials. The composite covariance matrix and its eigenvalue decomposition are given by

$$C_c = \bar{C}_1 + \bar{C}_2 \tag{2}$$

C_c can be factored as $C_c = U_c \lambda_c U_c^T$, where $U_c$is the matrix of eigenvectors and λ_c is the diagonal matrix of eigenvalues. Note that the eigenvalues are assumed to be sorted in descending order throughout this section.

The whitening transformation

$$P = \sqrt{\lambda_c^{-1}} U_c^T \tag{3}$$

equalizes the variances in the space spanned by the eigenvectors in U_c. In other words all eigenvalues of PC_cP^T are equal to one. If $\bar{C}_1$and $\bar{C}_2$ are transformed as

$$Q_1 = P\bar{C}_1P^T \text{ and } Q_2 = P\bar{C}_2P^T \tag{4}$$

then Q_1 and Q_2 share common eigenvectors, i.e.,

$$Q_1 = B\lambda_1B^T \text{ and } Q_2 = B\lambda_2B^T \text{ and } \lambda_1 + \lambda_2 = I \tag{5}$$

where I is the identity matrix. It is evident from equation (5) that the sum of two corresponding eigenvalues λ_1 and λ_2 is always one. Hence the eigenvector with largest eigenvalue of Q_1 is corresponding to the smallest eigenvalue of Q_2 and vice versa. This feature makes eigenvectors in B to be useful for discriminating two populations of EEG.

The inverse of CSP projection matrix $W_{csp} = B^TP$ contains the common spatial patterns and can be seen as time – invariant EEG source distribution vector.

III. EXPERIMENTAL PROCEDURE FOR DATA COLLECTION AND CONSTRUCTION OF CSP FOR VAM

In the current study, CSP maps were produced for VAM to investigate distinguishability of the Right Arrow Movement and the Down Arrow Movement. CSPs were generated from EEG data recorded from six volunteer subjects. The details of

EEG recording are given later in this section. First, EEG signals were amplified and then filtered using a Butterworth band pass filter (1– 40Hz). In order to improve the possibility of distinguishability, it was decided to construct CSP maps for various frequency ranges or bands. This way, specific frequency bands containing distinct information on the mental tasks can be identified. This information may also be useful in understanding neurophysiological origin of VAM mental tasks. Therefore, before applying CSP method described in the previous section, for each subject, EEG signals were filtered into nine frequency bands with equal bandwidths of 4Hz (i.e., 4 - 8Hz, 8 - 12Hz, …, 36 - 40Hz). Then CSP patterns of EEG corresponding to each band were generated separately and CSP maps were constructed.

Data in this investigation were collected from six healthy subjects ages 25 - 35 years and labeled as S1, S2…S6; four males (subjects: S2, S3, S4, and S6), and two females (subjects: S1 and S5), five of them are right-handed (subjects: S1, S2, S3, S5, and S6) while one of them is left handed (subject: S4) who took part in this study. Five subjects (S1 - S5) had previously participated in EEG recordings and were familiar with the experimental environment.

Subjects were screened initially and a short training was given in advance before real recording sessions were started. In training sessions, subjects were shown two animated images of a single arrow hitting a black square as in Table I. one representing DAM and the other representing RAM. These animated images would help them to visualize arrow movements cohesively during recording sessions.

During the recording, subjects were seated in an armchair and they were asked to keep their arms and hands relaxed and to avoid eye movements while keeping his/her eyes open during the recordings while looking at a black square pasted on a white blank screen which was placed approximately one and half meters away from the subject. A program called *Alarm* was developed for informing the subject about the forthcoming mental task to be recorded and assisting the subject with when the recording starts and when it ends. Each trial started with the *Alarm* program informing the subject verbally what mental task should be imagined in the upcoming trial. A short beep was made to inform the subject to start the mental task and at the end of a fixed period another beep (having different tone from the previous one) was produced to inform the subject to stop the mental task. If it is observed that eye blinks, eye moments or facial muscle movements occurred during the recording of the trial, data recorded in the trial is discarded and the trial is repeated.

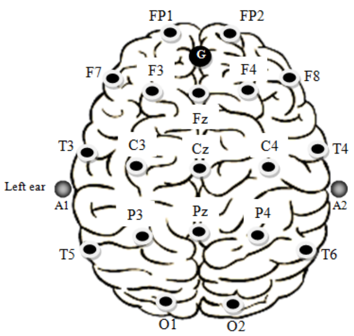


Fig. 1. Electrode positions of the 10-20 system

During all the experiments conducted for this research work, the EEG electrode placement used for data acquisition is based on standard international 10-20 system [25] and they are labelled as, Fp1, Fp2, F7, F3, Fz, F4, F8, C3, Cz, C4, P3, Pz, P4, T3, T4, T5, T6, O1, O2 and G (ground electrode). Typical 10-20 electrode placement system is given in figure. 1.

In addition to 20 EEG electrodes in the electro-cap, two ear electrodes have also been connected to the amplifier as reference electrodes.

We have followed the same experimental settings, recording parameters for both DAM and RAM mental tasks. The parameters and settings used in all the recording sessions are given in Table II.

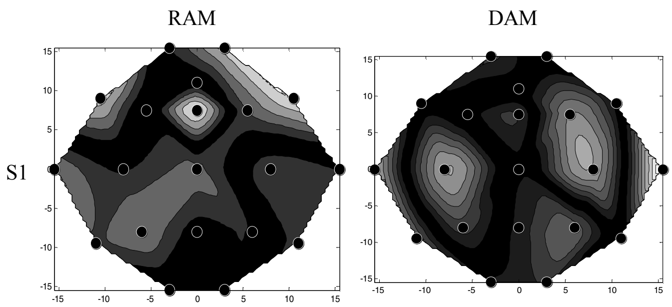
TABLE II
COMMON PARAMETERS AND SETTINGS USED IN THE RECORDING SESSIONS

Channels used for recording	All 20 channels according to 10-20 system
Sample rate	256 samples per second
Preparation period	5 seconds
Recording duration	9 seconds
Number of Subjects	06
Number of trials per mental task per subject	120 trials
Total number of mental tasks	02
Total number of trials used per subject for the CSP maps	240 trials
Total number of EEG data points used in the calculations	2048

IV. RESULTS

Spatial patterns calculated for each subject [i.e., the first and last columns of in ${W_{csp}}^{-1}$ for the subject] are shown in figure 2 and 3. The contour plots are obtained with cubic interpolation. Since within a CSP pattern the coefficients rarely cross the zero line, and for filtering, only the absolute values of the coefficients are important, the patterns are plotted in grayscale symmetric to zero for easy comparison.

As described in the previous section, separate CSP maps were produced for nine frequency bands for each subject. This produced 18 CSP maps (nine maps corresponding to DAM and nine maps corresponding to RAM) for each of the six subjects. First we analyzed these maps to find the best frequency band common to all six subjects which produce CSP maps where the two mental tasks can be distinguished.



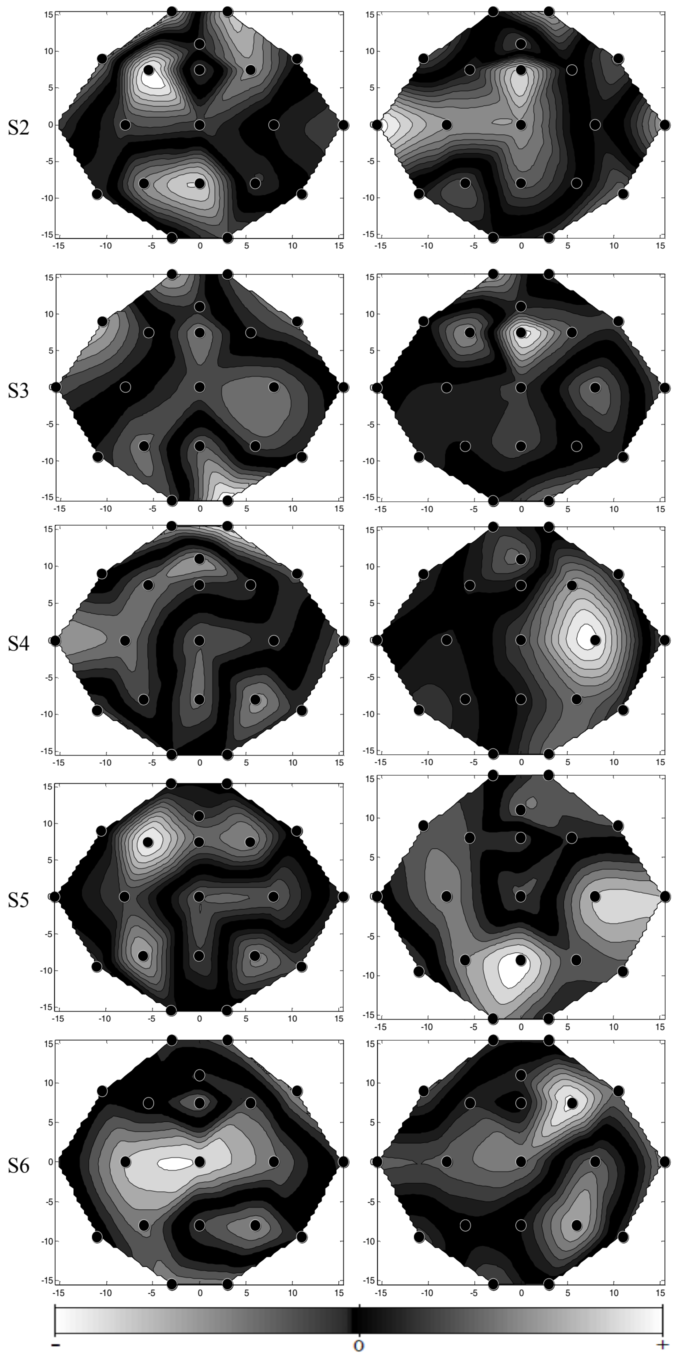


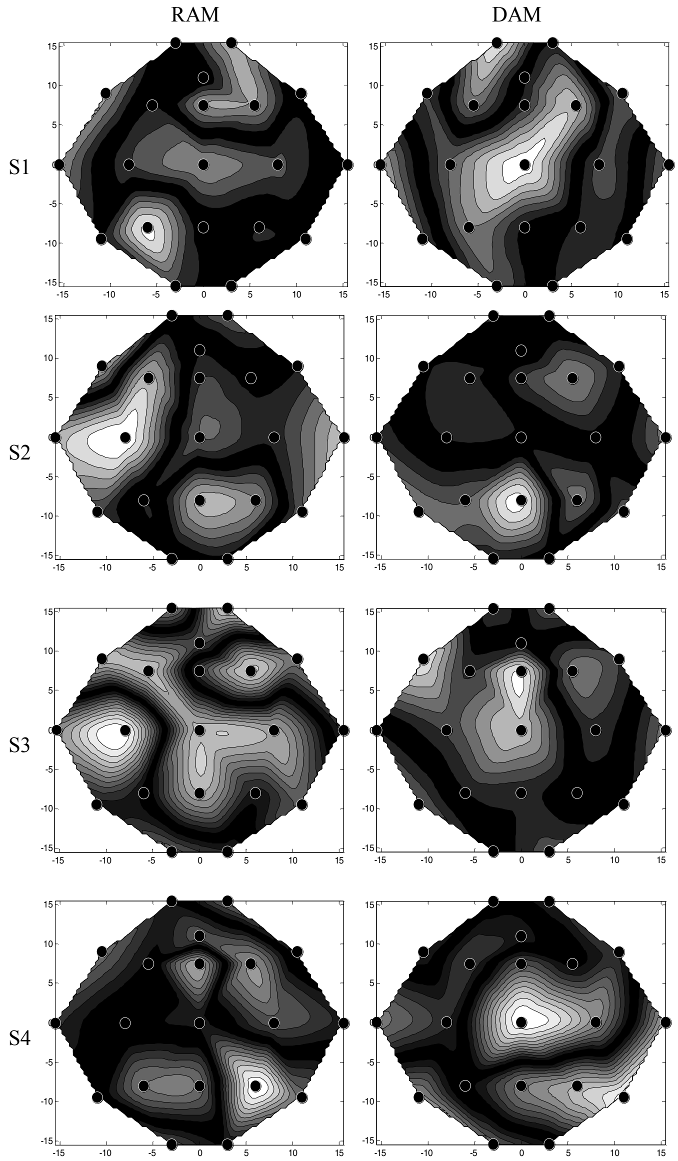
Fig. 2. Most important spatial patterns for distinguishing RAM from DAM for all six subjects in the fixed frequency range 16-20Hz. Only the absolute values of the coefficients are plotted.

TABLE III
DISCRIMINATING LOCATIONS OF RAM AND DAM FOR SIX SUBJECTS SHOWN IN FIG. 2

Subjects	RAM	DAM
S1	Fz	C3, C4, T4
S2	F3, Pz	Fz, T3
S3	O2	Fz
S4	G, T3, Pz, P4	C4
S5	F3, P3	Pz, C4
S6	Cz	F4

The best common frequency band found was in the middle Beta band (16-20Hz). The results are shown in figure 2. The figure 2 shows that for each subject, there is a clear distinction between patterns in the maps produced with DAM mental tasks and RAM mental tasks. However the patterns show variations from subject to subject. The locations of active areas of each map in figure 2 are listed according to subjects in Table III.

Secondly, we searched distinct patterns of DAM and RAM in CSP maps which are common to all the six subjects. Figure 3 shows the result of this search. However in this case the corresponding frequency bands show variations from subject to subject. It is evident from figure 3 that for DAM mental task, most of the subjects show activities along the central line of the scalp while for RAM mental task active areas are located off the central line either to the left or to the right depending on the subject.



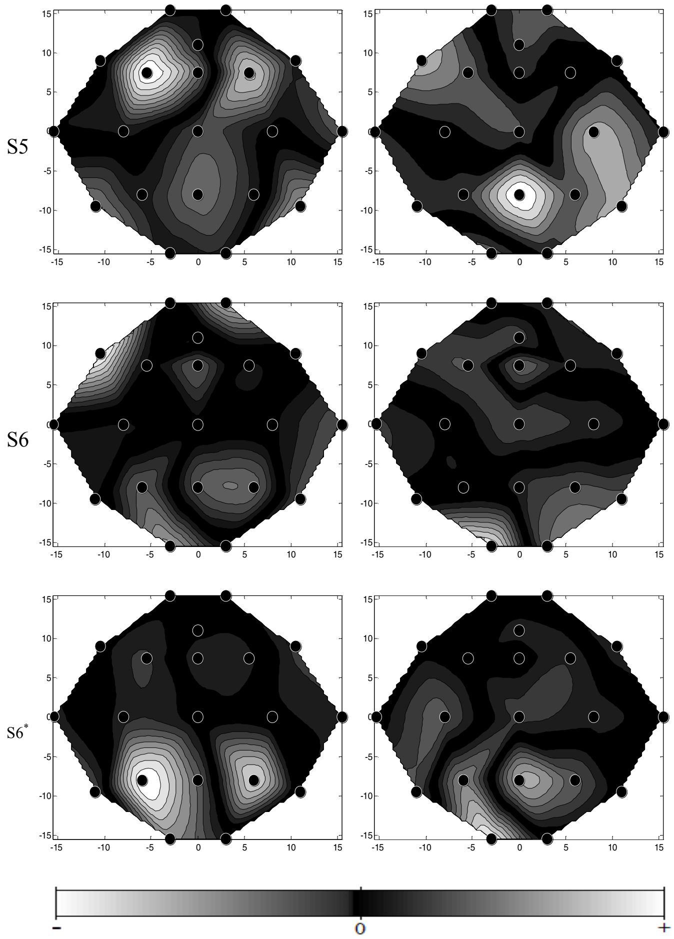


Fig. 3. Most important spatial patterns for distinguishing RAM from DAM for all the subjects. For subject S6 in addition to the most important spatial patterns, the second most important spatial patterns are also given under S6*. Only the absolute values of the coefficients are plotted.

In this study, it became very clear that although DAM and RAM produce activities in distinct areas of the scalp, the exact active locations and the frequency bands to be used in filtering depend on the individual subject. In other words, it is really necessary to determine suitable frequency bands for every subject during a pre training session of EEG recordings to find out the best frequency bands and the active EEG areas on the scalp of the subject. This information will be vital to have a reliable and effective BCI system.

V. Conclusion

In this paper we studied the CSP maps generated from equally divided nine frequency bands 4 - 8Hz, 8 - 12Hz,…, 36 - 40Hz and selected the optimal frequency bands for distinguishing the two mental tasks in VAM. For every subject participated in the study, the areas of the scalp which became active while performing the VAM were identified. These areas are found to be strongly dependent on individual subject as well as the frequency bands used for constructing the CSPs. This may be due to the fact that only a few EEG electrodes (20 electrodes) were used in this study. Usually good CSP maps for MI have been produced using large number of EEG electrodes (over 100 electrodes). Therefore we believe that the limited number of EEG electrodes used in this study is not adequate to make specific predictions on effective electrode locations corresponding to VAM. As a result definitive predictions on neurophysiological origin of VAM mental tasks cannot be made with CSPs constructed with limited number of EEG electrodes. However, optimal frequency bands identified for individual subjects in this work would be beneficial for preprocessing and classifying VAM mental tasks in a BCI environment. Next step in our investigation on identification of effective EEG channels and neurophysiological origin of VAM mental tasks is the construction of high resolution CSPs with large number of EEG electrodes.

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