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A SPACE-TIME-FREQUENCY ANALYSIS APPROACH FOR THE CLASSIFICATION MOTOR IMAGERY EEG RECORDINGS IN A BRAIN COMPUTER INTERFACE TASK

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Abstract— **We introduce an adaptive space time frequency analysis to extract and classify subject specific brain oscillations induced by motor imagery in a Brain Computer Interface task. The introduced method requires no prior knowledge of the reactive frequency bands, their temporal behavior or cortical locations. The algorithm implements an arbitrary time-frequency segmentation procedure by using a flexible local discriminant base algorithm for given multichannel brain activity recordings to extract subject specific ERD and ERS patterns. Extracted time-frequency features are processed by principal component analysis to reduce the feature set which is highly correlated due to volume conduction and the neighbor cortical regions. The reduced feature set is then fed to a linear discriminant analysis for classification. We give experimental results for 9 subjects to show the superior performance of the proposed method where the classification accuracy varied between 76.4% and 96.8% and the average classification accuracy was 84.9%.**

I. INTRODUCTION

THE use of the electrical activity of the brain for communication and control has gained significant interest in the last several years. The Brain Computer Interface (BCI) is constructed by recording and processing the electrical activity of the brain which is related to a specific mental activity [1]. Since this activity is produced without the need of any muscular act it has great potential for handicapped people to establish communication with their environment. A BCI can be constructed invasively by recording single neural activity [2] or noninvasively by recording EEG [1]. The invasive methods provide higher signal to noise ratio and have more spatial resolution however they have several clinical risks. The EEG based system is preferred in general because it is easy to construct and has minimal risk. The motor imagery (MI) based brain activity is used frequently to construct a BCI. During MI the subject is imagining a hand or finger movement, without any execution. The underlying basis of using MI in a brain computer interface is that the unilateral MI causes contralateral hemisphere preponderant event related synchronization (ERS) and desynchronization (ERD) [1]. The ERD and ERS patterns occur as an energy decrease and increase in the rhythmic components of EEG respectively. Several neuroscience studies have shown that the ERD and ERS in alpha (7-13Hz) and beta (14-32Hz) bands caused by the MI, as well as motor execution (ME), have different temporal characteristics [3]. In general the alpha band activity requires seconds to attenuate and recover whereas the beta band shows burst activity following an ERD [3]. In addition to neuroscience literature, many BCI studies have also shown that the ERD/ERS events have subject specific behavior. The selection of active bands with distinction sensitive learning vector quantization and the use of adaptive autoregressive parameters for the selection of best classification time point have emphasized the importance to adapt subject depended information in an automated manner in either time or frequency [4,5].

As a result, previous literature provides enough evidence that the brain oscillations can be characterized in space, time and frequency spread features. And it is also very important to consider that these features are subject specific. Therefore an ideal BCI system should consider space-time-frequency (s-t-f) features at the same time by adopting the physio-anotomical differences between the subjects. Recently time-frequency (t-f) analysis methods have been used to classify and visualize MI and ME related activities [6- 9]. In contrast to conventional methods where the classification is implemented with fixed windows or predefined frequency index, the main use of t-f methods in a BCI system is that they can account for multiple time-frequency indexes in the classification stage.

Here we investigate an approach which can deal with these problems without any need of priori information about the reactive frequency bands, their temporal behavior or cortical locations. The proposed signal processing and classification system first implements a discriminative t-f analysis on a multi-channel EEG data set. This step learns the most discriminant time segments for a given sensor space by implementing a merge/divide strategy in time axis and it is followed by a frequency domain clustering to select the most active frequency bands in each adapted segment. Then the most discriminant t-f patterns are sorted from sensors and processed by principal component analysis (PCA). Finally a linear discriminant analysis (LDA) was used to classify the

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reduced feature set. A block diagram of the proposed method is given in Fig. 1. This paper is organized as follows; in the next section we summarize the experimental paradigm. Then in section III we explain how to construct the adaptive time and frequency segmentations on multichannel EEG to extract subject specific information. In section IV we use PCA to reduce the dimensionality and decorrelate the feature set. Finally we use a linear discriminant for classification. In the results section we give experimental results from 9 subjects and compare our results with another space time and frequency weighting algorithm given in [9].

II. MULTICHANNEL MOTOR IMAERY EEG DATA

The dataset of BCI competition 2002, which was provided by Dr. Allen Osman from University of Pennsylvania, is used in this investigation [10]. The imagery EEG data was collected from 9 subjects. The subjects were asked to execute an imagined left and right index finger movement in an experimental paradigm given in Fig. 2. First the subjects are told whether the action will be explicit or imagined. Then a L/R cue appears on the screen indicating whether the movement is left or right. One second after the L/R cue, the letter X appears on the screen indicating it is time to take the required action. EEG was recorded with 100Hz sampling frequency from 59 electrodes placed on site corresponding to the International 10/20 system and referenced to the left mastoid. In this study the EEG data from 21 electrodes indicated in Fig. 2 are analyzed. These channels are converted to Hjort derivation in order to enhance the local activity [10]. The Hjort derivation C_i^H is calculated as

$$C_i^H = s_{C_i} - \frac{1}{4}\sum_{j \in S_i} s_{C_j} \tag{1}$$

where s_{C_i} is the reading of the center electrode C_i, with $i=1,2,..,21$ S_i is the index of 4 electrodes surrounding electrode C_i (c.f., Fig. 2). Then the EEG data is band pass filtered between 2-40Hz. For classification, we use all 90 trials available for each task.

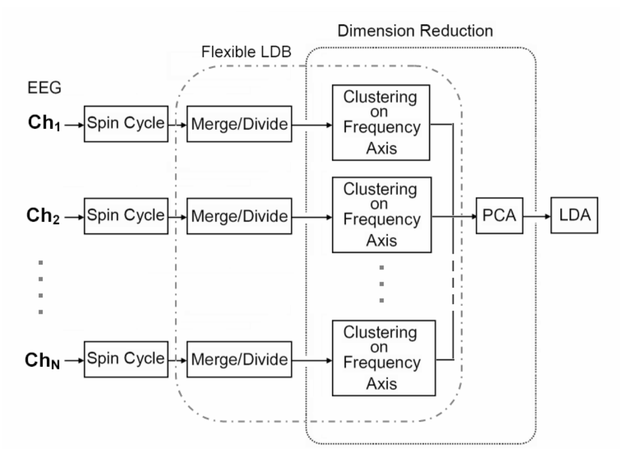
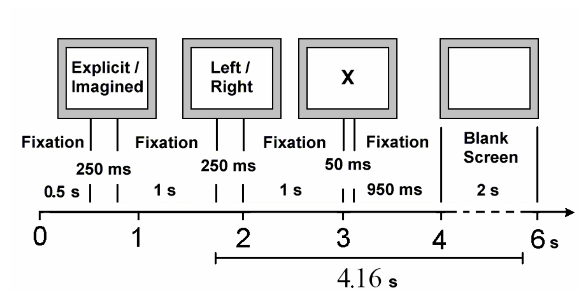


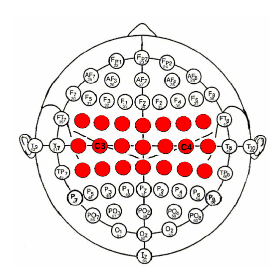
Fig. 1 - The block diagram of the proposed system (N=21).

III. ADAPTIVE TIME-FREQUENCY SEGMENTATION

As emphasized in the previous section the alpha and beta band ERD/ERS patterns have transient behavior. Therefore it is crucial to focus on the local properties of the EEG. The Local discriminant bases (LDB) algorithm [11] has been developed to extract such local information. The original LDB algorithm expands the signals of given classes into orthonormal bases by using wavelets or local trigonometric bases over a dyadic tree structure. It then finds the nodes of the tree where the classes are well separated by using a distance function maximization strategy [11]. Since the MI related ERD/ERS patterns appear as time locked transient phenomena, we use Local Cosine Packets (LCP) to describe the signal. However, subject specific EEG patterns will not necessarily fall in dyadic segments of the original LDB. Also it is difficult to capture the discriminant information in the EEG with individual expansion coefficients. Therefore we developed the Flexible-LDB algorithm which enhances the time segmentation procedure by adopting a merge/divide strategy which removes the limitations to dyadic segments [12]. Then it extracts most discriminant band features in each time segment with a frequency axis clustering procedure. Let us first shortly explain the time adaptation algorithm (for details see [12]). While constructing the segmentation in each iteration, the given signals are analyzed with three smooth windows which have a children and mother structure. Basically the mother time segment is the union of the children time segments. In each segment the signal is expanded using LCP which provides local spectral representation. Then the total distances



(a)



(b)

Fig. 2 - (a) The time course of the experimental paradigm. The analysis window is indicated at the bottom and includes the preparation stage as well. (b) 21 electrode locations are used in this study. The conventional C3 and C4 electrode locations are marked.

of the expansion coefficients between left and right classes are compared in the mother and children subspaces. Whenever the total distance of the children is greater than the mother space, the signal is divided at that point and mother segment is destroyed. Otherwise, the children segments are destroyed and mother segment is saved. In the next iteration, the mother segment is used as the left child. Note that the right child is the basic smallest size time segment used by the procedure and will have a fixed length. The left child can grow to be multiples of the basic smallest segment. This algorithm is iterated from left to right along the time axis by implementing the above procedure to achieve the desired time adaptation. This enabled us to locate discriminant ERD/ERS patterns that have different temporal behaviors.

The algorithm can be summarized as follows.

Step 1. Select a basic time window size and construct a children mother structure.

Step 2. In each space expand the signal into Cosine Packets. For each expansion coefficient calculate the distance between each class and accumulate the distances of expansion coefficients in each subspace.

Step 3. Merge the children subspaces if their discrimination power is less than that of the mother subspace; else divide the signal at that point.

Step 4. Go to step 1 and iterate the previous steps from left to right until the desired time adaptation is obtained.

There are various choices for distance measures. Assume p, q represent the cumulative probability distribution of each expansion coefficient estimated via a histogram. We have used the Euclidean distance

$$D(p,q) = \left\| p_i - q_i \right\|^2 = \sum_{i=1}^{n} \left(p_i - q_i \right)^2 \qquad (2)$$

for time segmentation. Further, we implemented the Fisher class separability criterion

$$F = \frac{\left(\mu_1 - \mu_2\right)^2}{\sigma_1^2 + \sigma_2^2} \qquad (3)$$

for ordering the features, where μ and σ are the mean and standard deviation of the feature they belong to.

IV. Feature extraction, dimension reduction and classfication

After completing the segmentation we can sort the individual expansion coefficients with a class separability criterion, here *F,* and use them for classification. We realize that such a direct sorting causes feature space with high dimensionality. A high dimension feature space can decrease the generalization capability of the classifier when there is a limited number of training samples available [13]. Also during our studies we observed that the center frequency of the oscillations differ from sweep to sweep. This increases uncertainty along the frequency axis. Therefore, we implement a frequency axis adaptation within each time segment; we merge coefficients that are adjacent in the frequency domain only if their union has a larger discrimination power than the individual coefficients. Note that this is basically a coefficient clustering approach obtained via cost function maximization and results in an adaptive frequency band adaptation for discrimination. See [12] for details.

Note also that Cosine Packet representations are not shift invariant. To get around this problem we implemented the "spin cycle" procedure of [11]. The procedure expands the training set by generating its time shifted versions in both directions in a circular manner. If the desired number of shifts is τ then the training set is expanded to $2\tau + 1$ including the original signal and its shifts by $-\tau, -\tau+1, ..., \tau$.

We use LDA as a classifier on the t-f features [13]. However one should note that due to the volume conduction, the neighbor cortical areas have correlated activity. Since *F* criterion does not take into account the correlations between ordered features, the same information can be repeated on the top features. Therefore, prior to entering the features to LDA we apply PCA on the top sorted features [13]. We expect that the PCA will remove the correlation between features and provide dimension reduction. Finally we supply this PCA re-ordered feature set to LDA.

V. Results

To assess the efficiency of the proposed algorithm we compared its performance to conventional C3/C4 electrode locations. We selected an analysis window of 416 samples and a tree depth of 4. The cell size for the merge/divide approach is chosen to be equal to the deepest segment, which is 260ms. For the PCA procedure, we typically select *k*=48 because most of the discrimination power is concentrated in these coefficients. We have used 10 times 10 fold cross validation to estimate the classification accuracy. Table 1 shows the classification accuracy for 9 subjects.

The proposed s-t-f analysis provided an average classification accuracy of 84.9%. Whenever the conventional C3/C4 electrode locations of a 10/20 system are used the classification performance drops to 80.6%. With the exception of subject S1, on all subjects the classification error decreased when more channels are used. Especially for subject S3, S4 and S8 the s-t-f approach has provided around 10% of improvement, also subject S7 has reached the maximum classification performance. We individually checked the discrimination power of each electrode location for these subjects. We have observed that the best discriminative locations are not always C3/C4 electrodes. In Fig. 3 we visualize the topographical distribution of discrimination power for subjects S7 and S8. When just C3/C4 electrodes were used a classification accuracy of 89% and 70% was obtained for these subjects. When 21 electrodes were used then the classification accuracy for each of these subject moved up to 96.8% and 80.1%. The topographical maps explain this improvement. As it can be seen from Fig. 3 the most discriminant locations are the neighbor areas of C3 and C4 electrode locations. Besides this, there exists a hemispherical asymmetry for subject S8. The ability to capture this asymmetry can be another advantage of achieving better classification rates.

The last point we would like to emphasize is the computational complexity and sensor selection capability of the introduced algorithm. The t-f segmentation steps are completed offline. After learning the most discriminative t-f segments and their electrode locations in an off line manner, one needs only to process the EEG data from the selected electrode locations in the on-line step. The processing includes calculating the expansion coefficients in priorly-learned segments and projecting them with a LDA. Since the discrimination power is calculated for each electrode location one can eliminate the electrodes which have no contribution to the classification and this may radically decrease the computational complexity.

In summary, we introduced an adaptive s-t-f analysis and feature selection approach for the classification of single trial multichannel MI related EEG recordings. We observed that the segmentations and feature characteristics calculated by our algorithm vary from subject to subject and depend on the spatial location in which the activity occurs. The algorithm has outperformed the standard 2-electrode approaches and a recently introduced t-f and space weighting algorithm in [9]. The obtained results are significantly better at $p<0.05$ and $p<0.03$ levels respectively (paired t-test). Its efficiency of constructing arbitrary tiling for each subject and space/electrode locations can be a reason for this. Obtained classification accuracy and capability of adapting to inter-subject variability and physio-anatomical differences make the proposed algorithm a promising candidate for future BCI systems.

TABLE I

THE CLASSIFICATION ACCURACY (%) OF THE INTRODUCED ALGORITHM (S-T-F) AND THE NUMBER OF FEATURES (NOF) USED TO ACHIEVE MINIMAL CLASSIFICATION RATE ARE GIVEN. THE TFW STANDS FOR THE RESULTS GIVEN IN [9]

	S-T-F				TFW
Subjects	21 electrodes	NoF	C3/C4	NoF	20 electrodes
S1	76.4	13	83.6	12	83
S2	94.3	12	92.6	29	91
S3	78.6	6	70	12	75
S4	81.6	14	70.7	25	78
S5	82	10	77.8	43	76
S6	88.4	10	87.2	9	77
S7	96.8	7	89.7	10	91
S8	80.1	6	70	43	71
S9	86.2	10	83.7	7	74
Avg	**84.9**	**9.8**	80.6	21	80

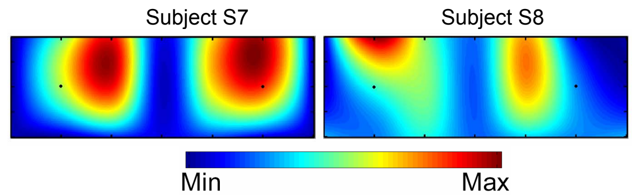


Fig. 3 – The topographical maps of 2 subjects estimated with the top 16 discriminant features. Cubic interpolation was used to visualize the discrimination power of 21 electrodes. Notice the differences between subjects and hemispheres. The C3/C4 electrode locations of the standard 10/20 system are marked with black dots.

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