Multi-channel Flexible Local Discriminant Bases for Classification of Left/Right Finger Movement Imagery Related EEG

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ABSTRACT

This paper presents a feature extraction scheme called multi-channel flexible local discriminant bases (MF-LDB) for left/right index finger movement imagery classification of a multi-channel electroencephalogram (EEG). The MF-LDB is obtained by calculating the local cosine packets (LCP) of the decided channel over nonuniform time-segments. The proposed method combines information from neighboring channels based on hard and soft decision. Simulation results show that the proposed feature extraction scheme can improve classification accuracies of the left/right index finger movement imagery signals by more than 3%. By applying the minimum variance distortionless response (MVDR) to find the spectra over nonoverlapping time-segments of each EEG channel, a nonredundant time-frequency transform called local MVDR packets transform which can provide highly selective frequency responses is also presented with approximately 4% improvement in classification accuracy.

Keywords: Left/Right imagery; Classification; Electroencephalogram (EEG); Local Discriminant Bases (LDB); Local Cosine Packets (LCP); Minimum Variance Distortionless Response (MVDR)

1. INTRODUCTION

Nowadays, a study on the brain computer interface (BCI) raises a lot of signal processing issues to be solved [1]. One of that is how to distinguish between the left and right motor imagery signals and correctly classify them. The possible applications of this issue are such as controlling the wheelchairs, mouse, or remote by using brain signals, e.g. electroencephalogram (EEG).

Distinguishing the left and right motor imagery EEG is possible since the event-related desynchronization and synchronization (ERD/ERS) patterns usually occur on the opposite sides of the imagination of a movement [2]. This observation on the ERD/ERS patterns motivates many researchers to explore novel theories and algorithms for left/right motor imagery EEG classification. In [3], a time-frequency based approach is proposed by filtering the fixed time windows in order to obtain band powers (BP) and classifying the resulting BP with the learning vector quantization (LVQ). Automated approach to adjust the influence of the BP during the learning process can be done using the distinction-sensitive learning vector quantization (DLVQ) instead of the LVQ [4]. An alternative way to obtain useful features for the classification is by employing parameters of the autoregressive (AR) model over uniformly short intervals [5]. To further improve [5], AR parameters are designed to be time dependent by using the model called adaptive autoregressive (AAR) [6]. Taking into consideration that the features in [4],[5],[6] are designed based on fixed time segments. Since the ERD/ERS patterns might not uniformly occur in time, the classification accuracy might be degraded in some cases. This problem can be efficiently solved by extracting the features of channels C3 and C4 of a multi-channel EEG based on the local discriminant bases (LDB) procedure derived from the local cosine packets (LCP) [7] over nonuniform time-segments [8],[9]. However, according to the studies in [2], the clear ERD/ERS patterns at different frequencies might not occur at the same spatial position (channel) on the human scalp. Since only channels C3 and C4 are used in [8],[9], the misclassification rates might be high in some sets of data. In [10], by incorporating more channels besides C3 and C4, the multi-channel classification scheme is illustrated but still yields insignificant improvements compare with those in [8]. For convenience, the classification scheme in [8] is called the conventional scheme.

This paper aims to improve the LDB in [8] by including more useful channels rendering a more efficient feature extraction scheme called multi-channel flexible local discriminant bases (MF-LDB). We also propose two methods to design the MF-LDB. For the first method called hard decision making (HDM), the MF-LDB is designed based on the channel that maximizes class separability. For the second method called soft decision making (SDM), the MF-LDB is designed based on linear combinations of the $\hat{M}$ channels which have the highest class separability. Since,

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the LCP used in the design process of the MF-LDB is not a shift invariant transform, spin cycle procedure [11] is employed. After that the important features are selected using Fisher class separability criterion and classified using the linear discriminant analysis (LDA) [12]. To further improve the classification accuracy, we propose a high resolution transform which motivated from the LCP and minimum variance distortionless response (MVDR) [13],[14] called local MVDR packets. The local MVDR packets transform is used instead of the LCP to design the LDB of the conventional scheme and yields approximately 4% improvement in classification accuracy.

2. BACKGROUNDS

This section provides some mathematical backgrounds used in this paper. Specifically, the derivations of the local cosine packets and the minimum variance distortionless response are presented.

2.1 Local cosine packets (LCP)

In this paper, we use a local cosine packets (LCP) to obtain the frequency representation of the signal. The LCP has several desirable properties. Similar to the short time Fourier transform (STFT), it is orthogonal, and has uniform partitioning in frequency domain with real transform coefficients, which are suitable to represent real signals with minimum redundancy. The LCP uses an overlapping window to reduce discontinuities between signal segments. Compared to wavelets, its basis functions share an equal length, and can be computed in a more efficient way using several existing fast discrete cosine transform algorithms.

Let $x(t)$ be a signal in time domain, and $[a_j, a_{j+1}]_{j\in Z}$ be a set of partitions of $x(t)$ where the length of each partition is $l_j = a_{j+1} - a_j$. LCP coefficients can be calculated by

$$C_k^j = \left\langle x(t), \psi_k^j(t) \right\rangle = \int_{a_j-\gamma}^{a_{j+1}+\gamma} x(t)\psi_k^j(t)dt, \qquad (1)$$

where

$$\psi_k^j(t) = w_j(t)\sqrt{\frac{2}{l_j}}\cos\left[\pi\left(k+\frac{1}{2}\right)\frac{(t-a_j)}{l_j}\right], j \in \mathrm{Z}, k \in \mathrm{Z}^+,$$

and γ is overlapping part of the window $w_j(t)$ which is less than or equal to l_j. To preserve the orthogonality, the smooth window function $w_j(t)$ is constructed using the cutoff function $b(t)$ which satisfies the following conditions:

$$\left|b(t)^2\right| + \left|b(-t)^2\right| = 1 \quad \text{for} \quad t \in \Re,$$

$b(t) = 0$ if $t < -1$ and $b(t) = 1$ if $t > 1$. The reader is referred to [7] for more details on the LCP.

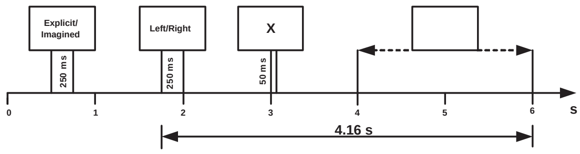


Fig.1: *Data acquisition stage of the EEG signal used for classification*

2.2 Minimum variance distortionless response (MVDR)

The minimum variance distortionless response (MVDR) can be used to estimate the spectrum of the time-domain signal $y(t)$ by employing the Fourier matrix into the optimization process [13]. Specifically, let $y(t)$, $t = 0, ..., \hat{T}-1$, be the signal obtained from passing a discrete time signal $x(t)$ to the length p bandpass filter $\mathbf{a} = [\mathbf{a(0)}, ..., \mathbf{a(p-1)}]^{\mathbf{T}}$ with center frequency at ω, where $\hat{T}$ is the length of the signal. Let $E[x(t)] = 0$, then the variance of $y(t)$ is

$$\sigma_y^2 = E[y(t)^2] = E[\mathbf{a^H x(t) x^H(t) a}] = \mathbf{a^H R_{xx} a}, \quad (2)$$

where $y(t) = \mathbf{a^H x(t)}$, H denotes the conjugate transpose operator, and $\mathbf{R_{xx}} = \mathbf{E[x(t)x^H(t)]}$. In order to design the filter $\mathbf{a}$ to be as selective as possible for the frequency band of interest ω, we can minimize the total power of $y(t)$ subject to the constraint that the filter is undistorted at the frequency ω. Specifically, we can find the filter $\mathbf{a}$ by the following contraint optimization problem:

$$\min\left\{\mathbf{a^H R_{xx} a}\right\} \quad \text{subject to} \quad \mathbf{a^H e}(\omega) = \mathbf{1}, \qquad (3)$$

where $\mathbf{e}(\omega) = [\mathbf{1}, \mathbf{e}^{-\mathbf{j}\omega}, ..., \mathbf{e}^{-\mathbf{j}\omega(\mathbf{p-1})}]^{\mathbf{T}}$. The minimization of (3) leads to

$$\mathbf{a} = \frac{\mathbf{R_{xx}^{-1} e}(\omega)}{\mathbf{e^H}(\omega)\mathbf{R_{xx}^{-1} e}(\omega)}. \qquad (4)$$

By substituting (4) into (2), the power of the resulting signal $y(t)$ after filtering with a bandpass filter $\mathbf{a}$ centered at ω can be obtained by

$$E[y(t)^2] = \frac{1}{\mathbf{e^H}(\omega)\mathbf{R_{xx}^{-1} e}(\omega)}, \quad 0 \le \omega \le \pi. \qquad (5)$$

According to (5), it can be shown in [16] that the spectrum of $x(t)$ can be estimated as

$$S(\omega) \approx \frac{p+1}{\mathbf{e^H}(\omega)\mathbf{R_{xx}^{-1} e}(\omega)}, \quad 0 \le \omega \le \pi, \qquad (6)$$

where p is the length of filter $\mathbf{a}$.

3. DATA ACQUISITION

The dataset used in this paper is obtained from the 2002 BCI competition [15]. This dataset contains nine subjects of 59-channel EEG at a sampling rate of 100 Hz. Each subject is asked to perform some specific tasks, e.g. push imagined left or right bottom. The experiment lasts for six seconds for each trial and 4.16-second signals after the appearance of the left/right cues are used for the classification (Fig. 1). The Hjort derivation [17] is applied to each channel, $\mathbf{e_i}$, in order to obtain local activities. The resulting channel after performing the Hjort derivation, $\mathbf{e_i^{Hjort}}$, can be approximated as follows:

$$\mathbf{e_i^{Hjort}} = \mathbf{e_i} - \frac{\mathbf{1}}{\mathbf{4}} \sum_{\mathbf{j} \in \mathbf{N_i}} \mathbf{e_j}, \tag{7}$$

where N_i denotes the indices of four neighboring channels of $\mathbf{e_i}$. The EEG signals are then filtered to retain frequencies between 2-40 Hz which are found to be a meaningful frequency range used in the analysis of EEG [1], [2]. In this paper, all one hundred and eighty trials (ninety trials of left and right imagery signals) are used for the classification.

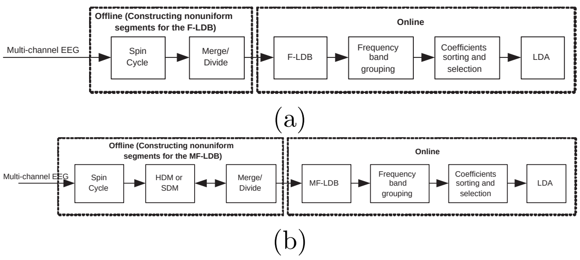


Fig.2: *Block diagram of (a) the conventional left/right index finger movement imagery classification method [8] and (b) the proposed classification methods.*

4. CONVENTIONAL EEG CLASSIFICATION METHOD

This section reviews the conventional method for left/right index finger movement imagery classification of EEG signals proposed in [8]. The block diagram of the conventional classification methods is shown in Fig. 2(a). The LDB which designed over the nonuniform time-segments obtained from the LCP called flexible local discriminant bases (F-LDB) is used as a feature extraction procedure.

4.1 Flexible local discriminant bases (F-LDB)

The design of the F-LDB is composed of two main components: 1) *spin cycle procedure* [11] which is used to eliminate the shift variant issue of the LCP, and 2) *merge and divide procedure* which is used to find the optimal nonuniform time-segments for the F-LDB which result in features that maximize the class separability. This procedure can be summarized as follows:

1. Divide the EEG signals into small uniform time-segments (up to the required frequency resolution), calculate their LCP coefficients and construct children and mother structures as shown in Fig. 3(a), e.g. $\mathbf{M_1}$ is a mother segment with the corresponding two children segments $\mathbf{y_1}$ and $\mathbf{y_2}$,
2. For each mother segment and its corresponding two children segments, calculate the Euclidean distances of the cumulative distribution functions (cdf-distances) [11] of their LCP coefficients as the class separability,
3. Merge the children segments if the sum of their distances is less than the distance of their corresponding mother segment, otherwise divide the signal at that point,
4. Continue the previous step from left time-segments to right time-segments until nonuniform time-segments are obtained.

4.2 Feature extraction, dimension reduction and classification

Once the nonuniform time-segments are obtained from the merge and divide procedure, the LCP coefficients calculated over the nonuniform time-segments are used as the features for the classification. However, we cannot use all features we have because of the curse of dimensionality [12]. Thus, we group LCP coefficients of channels C3 and C4 together into frequency bins and sort them using the Fisher class separability criterion:

$$F = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}, \tag{8}$$

where μ_i and σ_i^2 are mean and variance of the feature vector of class i. The top l coefficients will be further used as the selected features for classification. Linear discriminant analysis (LDA) [12] is used as a classifier. It is noted that the design process of the F-LDB can be implemented offline. For an online process, the designed F-LDB is used for extracting the features.

5. MULTI-CHANNEL FLEXIBLE LOCAL DISCRIMINANT BASES (MF-LDB)

Unlike the F-LDB, we propose the local discriminant bases which also take into account channels besides C3 and C4 called multi-channel flexible local discriminant bases (MF-LDB). In other words, channels of interest COI_{C3} in Fig. 3(c) and COI_{C4} in Fig. 3(d) are used to design the MF-LDB. Based on the problem formulation, we suggest two possible methods to design the MF-LDB named HDM and SDM. For simplicity, let us consider using only the COI_{C3} for describing our decision making methods in sections 5.1- 5.3

5.1 Problem formulation

Since the ERD/ERS patterns of each frequency band of EEG usually occur at different scalp locations, using more than just C3 and C4 electrodes

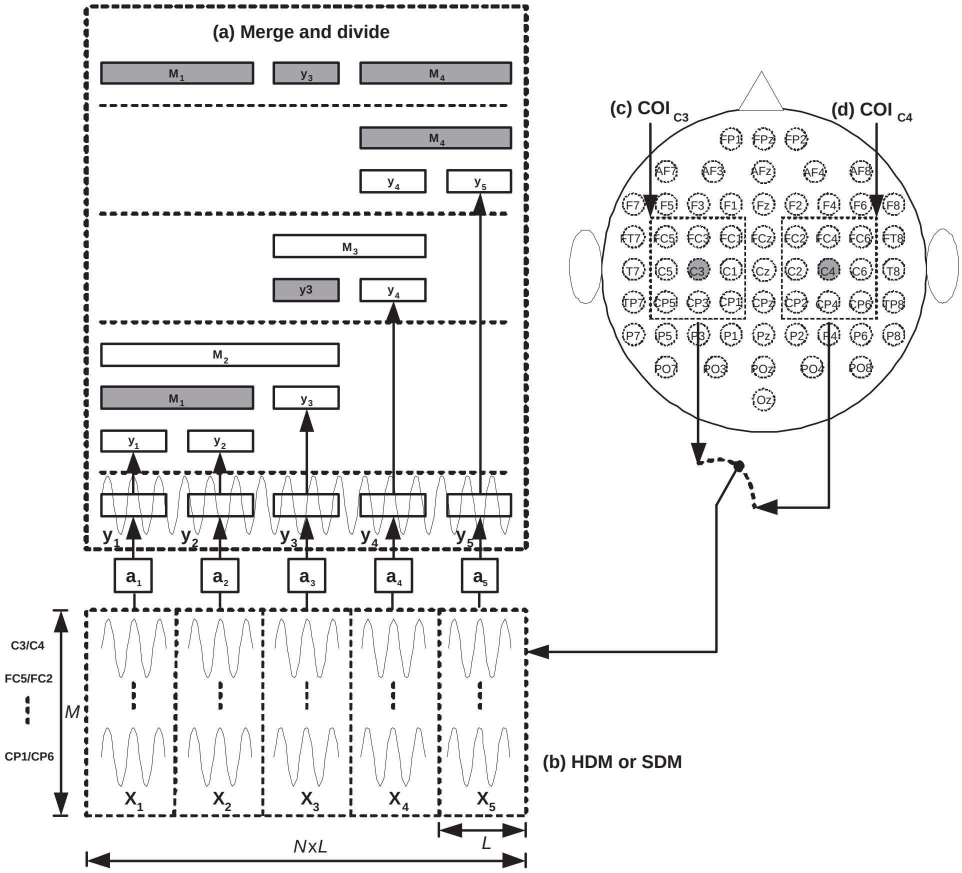


Fig.3: *Design process of the MF-LDB: (a) merge and divide procedure, (b) HDM or SDM, (c) COI$_{C3}$, and (d) COI$_{C4}$.*

may improve the classification performance in some situations. Thus, the MF-LDB which is an adaptive method that takes into account multi-channel EEG can be formulated as follows:

Let the $M \times L$ matrix $\mathbf{X_n}$ be the n-th time-segment of a length-L M-channel signal (Fig.3(b)), and let the length-M vector $\mathbf{a_n}$ be the corresponding weight vector of the n-th segment of M-channel signal where $n = 1, ..., N$, N is the number of all children segments (according to the merge and divide procedure), and M is the number of channels of interest. According to Fig.3(c), M is nine. Furthermore, let a length-L vector $\mathbf{y_n}$ be an input n-th children segment of the merge and divide procedure, then

$$\mathbf{y_n} = \mathbf{X_n^T a_n}. \tag{9}$$

In this section, we propose two efficient methods to find $\mathbf{a_n}$: HDM and SDM.

5.2 Hard Decision Making Method (HDM)

In this method, the MF-LDB is designed based on a channel that maximizes the cdf-distance of LCP coefficients between two classes (left and right index finger movement imagery signals). This method is called *Hard Decision Making method (HDM).*

For the n-th time-segment, $a_n(m)$ (the element of $\mathbf{a_n}$ corresponding to channel-m) can be set to one when m denotes the channel that maximizes the cdf-distance between two classes, otherwise $a_n(m)$ is zero. However, given the prior knowledge that C3 is known as the significant channel in which ERD/ERS patterns usually clearly occur, we can improve the decision making by giving more priority to this particular channel, i.e. the threshold α needs to be included in the decision making method. Specifically, let $m \in$ COI$_{C3}$,

1) if m is channel C3,

$$a_n(m) = \begin{cases} 1, & \text{if} \quad \|p_n^m - q_n^m\|^2 \geq \alpha \left\|p_n^{\hat{m}} - q_n^{\hat{m}}\right\|^2, \\ 0, & \text{otherwise,} \end{cases}$$

2) if m is not channel C3,

$$a_n(m) = \begin{cases} 1, & \text{if } \alpha \|p_n^m - q_n^m\|^2 \geq \alpha \left\|p_n^{\hat{m}} - q_n^{\hat{m}}\right\|^2 \geq \left\|p_n^{C3} - q_n^{C3}\right\|^2, \\ 0, & \text{otherwise,} \end{cases}$$

where $\hat{m} \in$ COI$_{C3} \setminus \{$C3$\}$. p_n^j and q_n^j denote the cdf-distances of LCP coefficients of channel-j of the n-th time-segment of classes 1 and 2 data, respectively. α is the setting threshold ranging form zero to one.

5.3 Soft Decision Making Method (SDM)

Basically, EEG signals can be modeled as the sum of neural potentials. By assuming that the clear ERD/ERS patterns might not exactly occur at any position of COI_{C3}, a soft decision making method (SDM) is proposed to construct the signal $\mathbf{y_n}$ at a new position that maximizes the cdf-distance by linearly interpolating the channels selected from COI_{C3}. Hence, $a_n(m)$ can be considered as the weight of channel-m of the n-th time-segment used for linear interpolation. Similar to HDM, given a prior knowledge that C3 is known as a significant channel in which ERD/ERS patterns usually occurs, the threshold β (ranging from zero to one) also needs to be employed in the decision making method. Specifically, let the set of the first $\hat{M}$ channels that maximize the cdf-distance denotes as $\overline{\mathrm{COI}}_{C3}$ where $\overline{\mathrm{COI}}_{C3} \subseteq \mathrm{COI}_{C3}$. A new channel (named $\tilde{m}$) is constructed by calculating the linear interpolation among all $m \in \overline{\mathrm{COI}}_{C3}$ by using $a_n(m)$ as their corresponding weights:

$$a_n(m) = \frac{\|p_n^m - q_n^m\|^2}{\sum_{i \in \overline{\mathrm{COI}}_{C3}} \|p_n^i - q_n^i\|^2}. \qquad (10)$$

After that two conditions need to be checked in order to obtain $\mathbf{y_n}$.

1) If $\beta \left\|p_n^{\tilde{m}} - q_n^{\tilde{m}}\right\|^2 \geq \left\|p_n^{C3} - q_n^{C3}\right\|^2$, $\mathbf{y_n}$ can be obtained by (9) using the resulting $\mathbf{a_n}$ from (10).

2) If $\beta \left\|p_n^{\tilde{m}} - q_n^{\tilde{m}}\right\|^2 < \left\|p_n^{C3} - q_n^{C3}\right\|^2$, channel C3 is selected as $\mathbf{y_n}$ without performing any interpolation.

Similarly, HDM and SDM are also separately applied to COI_{C4} in Fig.3(d). The resulting children segments from HDM or SDM are used as the input of the merge and divide procedure (section 4.1). Once the nonuniform time-segments and their corresponding LCP coefficients are obtained, we group the LCP coefficients obtained from both COI_{C3} and COI_{C4} together into frequency bins and sort them using the Fisher class separability criterion in (8). The top k coefficients will be further used as the selected features for classification. It is noted that the process of designing the MF-LDB can be implemented offline, hence the complexity of the online process (feature extraction, dimension reduction and classification) is the same as that of the conventional method.

5.4 Summary of the classification methods using HDM and SDM-based MF-LDB

The block diagram of the proposed classification methods is shown in Fig. 2(b). It can be summarized as follows:

1. Construct nonuniform time-segments for the MF-LDB from both COI_{C3} and COI_{C4} using HDM or SDM together with the merge and divide procedure as an offline process,
2. As an online process, calculate the LCP coefficients according to the resulting MF-LDB from 1.,
3. Group the LCP coefficients into selected frequency bins. (Normally, nonuniform frequency bins can be designed offline so that the class separability is maximized, but, experimentally, it yields only slightly improvement in classification accuracies (while consumes much higher computational complexity) over using the uniform ones [9]. Since the ERD/ERS patterns are proved to be mostly occurred in the mu and beta bands [2], hence, in this paper, only two fixed frequency bins of 8-12 and 16-20 Hz which correspond to the mu and beta bands, respectively, are employed).
4. Sort the resulting coefficients from 3. by Fisher class separability in (8) and select the top l coefficients as the selected features for classification,
5. Perform classification using the LDA with 10-fold cross -validation.

As mentioned, since the LCP is not a shift invariant transform, we also employ the spin cycle procedure, i.e. we also include the shifted versions (by $-\tau, ..., \tau$, in this paper, $\tau = 3$ is used) of the signals in COI_{C3} and COI_{C4} for designing the MF-LDB.

5.5 Local MVDR packets

In [8], the LCP is found to be useful for the left/right index finger movement imagery EEG classification. Since the LCP is one type of the time-frequency nonredundant transform which is independent from the data, it is interesting to develop a transform with similar properties but can be designed based on the input data. By calculating the spectrum of each nonoverlapping segment using the minimum variance distortionless response (MVDR) [13], [14], a new time-frequency nonredundant transform which takes into account information of the input data is proposed called local MVDR packets. Specifically, let $x(t)$ be a real discrete time signal of length $\hat{T}$ where $t = 0, ..., \hat{T} - 1$, the local MVDR packets coefficient at a translation index k and a frequency index ω can be approximately obtained by

$$S(k, \omega) = \frac{p+1}{\mathbf{e^H}(\omega)\mathbf{R_{xx}^{-1}}(\mathbf{k})\mathbf{e}(\omega)}, \qquad (11)$$

where $\mathbf{e}(\omega) = [\mathbf{1}, \mathbf{e^{-j\omega}}, ..., \mathbf{e^{-j\omega(p-1)}}]^{\mathbf{T}}$, p denotes length of a local basis of the MVDR (length of the filter), and the autocorrelation matrix $\mathbf{R_{xx}}(\mathbf{k})$ of size $p \times p$ can be estimated as

$$\mathbf{R_{xx}}(\mathbf{k}) = \sum_{\mathbf{t=n_k+p}}^{\mathbf{n_{k+1}}} [\mathbf{x(t-1)...x(t-p)}]^{\mathbf{T}} [\mathbf{x(t-1)...x(t-p)}],$$

where $0 \leq k \leq K-1$, n_k denotes the time index which the segmentation is performed with $n_0 = 0$, and $n_K = \hat{T}$. In practice, in order to avoid from being singular, $\mathbf{R_{xx}}(\mathbf{k})$ needs to be added by a matrix $\epsilon\mathbf{I}$ where $\mathbf{I}$ is the $p \times p$ identity matrix and ϵ is a very small positive number. The MF-LDB can also be obtained from the local MVDR packets by using HDM or SDM followed by the merge and divide procedure.

Intuitively speaking, the windowed cosine basis of the LCP is actually a fixed bandpass filter. By using the local MVDR packets, we can specifically design a more frequency selective bandpass filter in which the information would not be distorted at our particular frequency of interest ω. Therefore, the contribution of each resulting extracted feature would be less overlapped.

6. SIMULATION RESULTS

In this section, we use our proposed methods to distinguish between the left and right index finger movement imagery signals. Four out of nine subjects of the dataset in [15] which contains 59-channel EEGs at the sampling rate of 100 Hz are used. These four subjects are selected since they result in low classification accuracies in [8].

6.1 Design example of HDM and SDM

Let us consider subject nine in the experiment. Channel C4 and its neighboring channels (see Fig. 3(d)) are used to illustrate the uses of HDM and SDM for designing the MF-LDB. The resulting children segments obtained from the HDM (using threshold $\alpha = 0.8$) and SDM ($\beta = 0.8$ and $\hat{M} = 4$) compared with the conventional method are illustrated in Fig. 4. By using HDM (Fig. 4(b)), the 2-nd, 5-th and 12-th segments are chosen from channels C2, C2, and CP4, respectively, while the rests are chosen from channel C4. By using SDM (Fig. 4(c)), all children segments except the 2-nd, 5-th and 12-th segments are chosen from channel C4. The 2-nd segment is obtained by the weighted average of channels C2, FC2, CP2 and FC4. The 5-th segment is obtained by the weighted average of channels C2, CP2, C4 and FC4. The 12-th segment is obtained by the weighted average of channels CP4, C2, CP2 and C4. By using the merge and divide procedure, the resulting nonuniform segments obtained from using HDM and SDM are illustrated in Figs. 5(b) and (c), respectively, compared with the conventional method (Fig. 5(a)).

HDM and SDM result in visually clearer ERD/ERS patterns (as shown in Figs. 4(b) and (c), respectively) compared with the original children segments obtained only from channel C4 (Fig. 4(a)). Consequently, more efficient nonuniform segments so that the ERD/ERS patterns are clearly partitioned can be observed in Fig. 5. In addition, HDM and SDM yield similar nonuniform segments.

6.2 Classification accuracy

Table 1 illustrates the classification accuracies of HDM and SDM methods compared with the conventional method in [8]. Using both SDM and HDM consistently outperform the conventional method with the average of 4% and more than 5% in some subjects. Moreover, with less average number of features (NoF), using SDM yields a slightly higher average classification accuracy than HDM. According to Table 1, two things should be noted:

Table 1: *Classification accuracy (Acc %) of the proposed methods using the HDM and SDM compared with the method in [8] denoted as conventional (NoF denotes number of features).*

	HDM		SDM		Convent.	
Sub.	Acc	NoF	Acc	NoF	Acc	NoF
S3	74.44	20	75.56	4	72.22	5
S4	72.78	11	71.11	16	67.22	17
S8	68.89	16	70.56	8	65.00	13
S9	75.56	14	75	15	70.56	12
Avg.	72.91	15.25	73.05	10.75	68.75	11.75

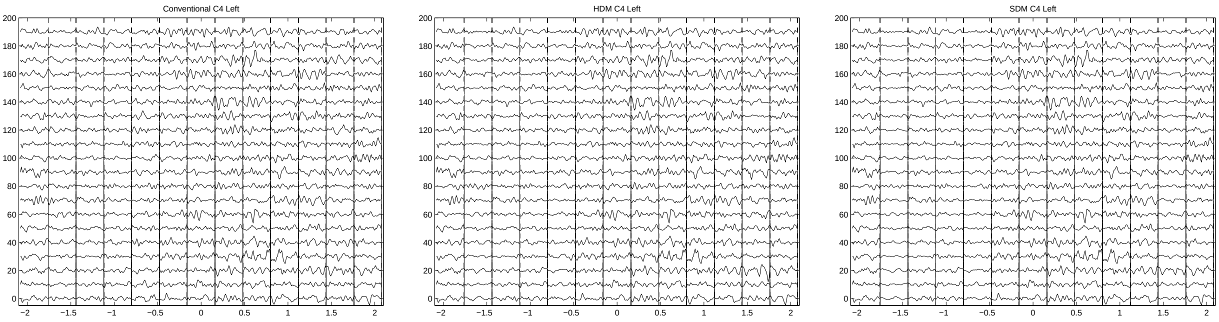
Table 2: *Classification accuracy (%) of subject 9 (S9) using the LCP and local MVDR packets.*

NoF	10	12	14	16	18	20
LCP	67.78	70.56	70	69.44	68.89	68.89
MVDR	73.89	72.78	72.78	75	72.78	72.22

- The classification accuracies of the conventional method obtained in this paper are slightly different from the ones obtain in [8] because 1) we dropped the used of principal component analysis (PCA) in order to clearly see the effect of the MF-LDB compared with the F-LDB, 2) only two frequency bins corresponding to mu and beta bands are employed since we would like to illustrate that ERD/ERS patterns found in these bands but might not occur at the same position on the human scalp.
- We only compare our results with the conventional method since [8] reported that the conventional method can achieve slightly better average performance than that of [10] for this particular dataset.

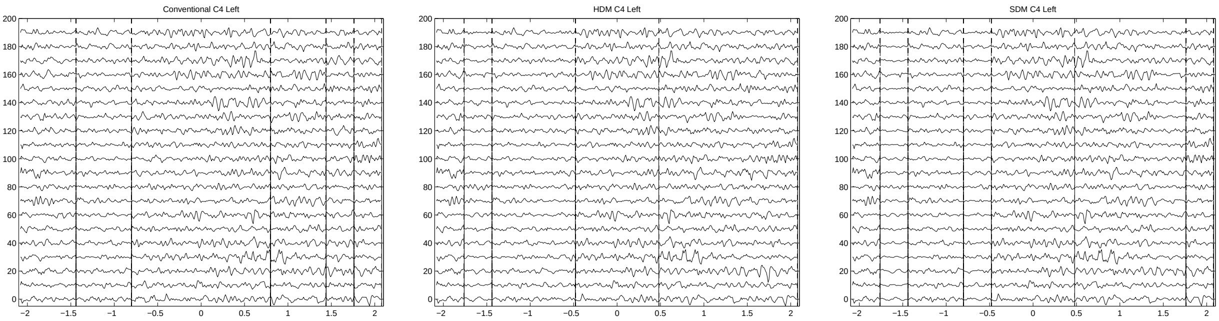
The proposed classification method can be further improved by 1) including new COIs as suggested in [10], 2) using the PCA to reduce the number of features, and 3) including more frequency bands besides mu and beta.

Moreover, by replacing the LCP in Fig. 2(a) with the local MVDR packets, classification accuracy of subject 9 is shown in Table 2. Since the local MVDR packets transform results in highly selective bandpass filters, it yields around 4% higher in classification accuracy than the LCP. It should be noted that, even though, using the local MVDR packets leads to an improvement in classification accuracy, the computational loads are quite high compared with the LCP. Reducing the complexity requires further investigations.



(a) (b) (c)

Fig.4: *Examples of the left finger movement imagery signals: (a) Original children segments , (b) resulting children segments using HDM of channel C4 and its neighboring channels, and (c) resulting children segments using SDM of channel C4 and its neighboring channels. Only 20 trials (with the mean shift by a multiple of 10) of each type of signals are shown for better visualization. x-axis represents the 4.16-second time interval as shown in Fig. 1, where 0 corresponds to 3.83 second in Fig. 1.*



(a) Conventional (b) HDM (c) SDM

Fig.5: *Examples of the resulting nonuniform time-segment (used for constructing the MF-LDB) after applying merge and divide procedure. Only 20 trials (with the mean shift by a multiple of 10) of each type of signals are shown for better visualization. x-axis represents the 4.16-second time interval.*

7. CONCLUSIONS

We have presented a data dependent feature extraction scheme for classification of a left/right index finger movement imagery multi-channel EEG called MF-LDB. Two methods, called HDM and SDM, are proposed for designing the MF-LDB. Besides using two fixed channels, these methods also employ other neighboring channels resulting in improvements of classification accuracies over the conventional scheme. The improvements from the proposed scheme support the previous studies that the ERD/ERS patterns in mu and beta bands may not occur at the same position on the human scalp. Furthermore, we have presented a novel local MVDR packets transform which is designed based on input data rendering highly selective frequency responses. Since the use of the local MVDR packets instead of the LCP leads to the improvement in classification accuracy, frequency band selection has a direct effect on extracting the important features of the ERD/ERS patterns.

8. ACKNOWLEDGEMENT

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