Proceedings of International Joint Conference on Neural Networks, San Jose, California, USA, July 31 – August 5, 2011

Filter Bank Feature Combination (FBFC) approach for Brain-Computer Interface

Zheng Yang Chin, Kai Keng Ang, Cuntai Guan, Chuanchu Wang, Haihong Zhang

***Abstract*— The Filter Bank Common Spatial Pattern (FBCSP) algorithm constructs and selects subject-specific discriminative CSP features from a filter bank of spatial-temporal filters in a motor imagery brain-computer interface (MI-BCI). However, information from other types of features could be extracted and combined with CSP features to enhance the classification performance. Hence this paper proposes a Filter Bank Feature Combination (FBFC) approach and investigates the use of CSP and Phase Lock Value (PLV) features, where the latter measures the phase synchronization between the EEG electrodes. The performance of the FBFC using CSP and PLV features is evaluated on four-class motor imageries from the publicly available BCI Competition IV Dataset IIa. The experimental results showed that the proposed FBFC using CSP and PLV features yielded a significant improvement in cross-validation accuracies on the training data (*p*=0.008) and better session-to-session transfer accuracies to the evaluation data compared to the use of CSP features using the FBCSP algorithm. This motivates the research of FBFC using a battery of other features that could possibly benefit EEG-based BCIs and multi-modal BCI systems.**

I. Introduction

In the use of an electroencephalogram (EEG)-based Motor Imagery Brain-Computer Interface (MI-BCI), the subject performs the imagination of movement from the first-person perspective without actually executing it [1]. As illustrated in the human homunculus [2], different body parts have a spatially ordered layout in the primary cortex. Hence, the imagination of different body part movements such as the hands, feet or tongue induces spatial changes in the EEG.

To discern these spatial changes in the EEG to the types of motor imagery action, various signal processing and machine learning algorithms have been proposed. Such methods extract useful information from the EEG as feature vectors, for example, band power estimates [3], autoregressive (AR) models [4], Phase Lock Value (PLV) [5] and Common Spatial Pattern (CSP) [6]. The PLV feature quantifies the phase synchronization between the EEG electrodes, and results suggest that it contains useful information for discerning the types of motor imagery action [7]. The CSP algorithm computes spatial filters that maximize the variance between two conditions such as left-hand and right-hand motor imagery. However, as the effectiveness of the CSP algorithm depends on subject-specific temporal filtering parameters, the Filter Bank Common Spatial Pattern (FBCSP) algorithm was proposed to address this issue [8]. The FBCSP algorithm autonomously performs the selection of key temporal-spatial discriminative CSP features that are specific to a subject. This algorithm yielded the best classification performance relative to the other submissions in the four-class motor imagery data from the BCI Competition IV [9] Dataset IIa [10].

Several feature combination approaches have been explored to improve the performance of MI-BCI in the literature. In [11], the gamma band power estimates feature were combined with the slow cortical potentials (SCP) feature to yield better performance than the use of only the SCP feature. In [12], [13], the Autoregressive (AR) feature, CSP feature and movement related potential (MRP) feature were combined using various strategies and yielded improved performance compared to the use of the individual features. In [5], [14], the PLV feature and the band power estimates feature were combined and also yielded improved performance compared to the use of the individual features. Thus the feature combination approach enhances the MI-BCI classification performance.

However, the FBCSP algorithm employs the filter bank approach to extract only CSP features. Hence, this paper proposes a Filter Bank Feature Combination (FBFC) approach and investigates the use of the CSP features and the PLV features. The FBFC approach employs a four-stage process: First, band-pass filtering using a filter bank to extract frequency components of the EEG; Second, feature extraction to extract different types of EEG features; Third, feature combination to select the most informative features from each type of feature using a mutual information criterion and to perform feature transformation; Finally, classification is performed on the transformed feature vectors. The performance of the proposed FBFC employing the CSP features and the PLV features is investigated and compared with the FBCSP algorithm employing only the CSP feature, on the four-class single trial motor imagery data from the publicly available BCI Competition IV dataset IIa [10].

II. Filter Bank Common Spatial Pattern (FBCSP)

The FBCSP algorithm [8] comprises four stages that

This work was supported by the Science and Engineering Research Council of A*STAR (Agency for Science, Technology and Research), Singapore.

Z. Y. Chin, K. K. Ang, C. Guan, C. Wang and H. Zhang are with Institute for Infocomm Research, Agency for Science, Technology and Research (A*STAR), 1 Fusionopolis Way #21-01 Connexis (South Tower) Singapore 138632 (email: {zychin, kkang, ctguan, hhzhang, ccwang}@i2r.a-star.edu.sg).

perform an autonomous selection of subject-specific temporal-spatial discriminative EEG characteristics for two-class MI-BCI, shown in Fig. 1.

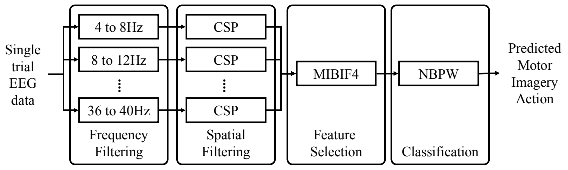

Fig. 1: Architecture of the Filter Bank Common Spatial Pattern (FBCSP) algorithm for two-class motor imagery EEG data. MIBIF4 and NBPW represent the Mutual Information Best Individual Feature and the Naïve Bayes Parzen Window classifier respectively.

A. *Band-pass filtering*

The first stage employs 9 band-pass filters that decompose the EEG into its respective frequency components from 4-8Hz, 8-12Hz, …, 36-40Hz. Various configurations of the filter bank are as effective, but these band-pass frequency ranges are employed as they cover the range of 4-40Hz and encompasses the *alpha*/*mu* and *beta* bands. These frequency bands have been shown to exhibit Event-Related Desynchronization / Synchronization (ERD/ERS) effects during motor imagery [13], [15], [16].

B. *Spatial filtering and feature extraction*

The second stage performs spatial filtering using the CSP algorithm [6] by applying a linear transformation on the EEG

$$\mathbf{Z}_{b,i} = \mathbf{W}_b^T \mathbf{E}_{b,i}\,, \tag{1}$$

where $\mathbf{E}_{b,i} = \left[\mathbf{e}_{b,1}^T, \mathbf{e}_{b,2}^T, \ldots, \mathbf{e}_{b,c}^T\right]^T \in \mathbb{R}^{c\times\tau}$ denotes the i^{th} single-trial EEG from the b^{th} band-pass filter; $\mathbf{e}_{b,l} = \left[e_{b,l}(1), e_{b,l}(2), \ldots e_{b,l}(\tau)\right] \in \mathbb{R}^{1\times\tau}$ denotes the filtered EEG signal from the l^{th} EEG channel; $\mathbf{Z}_{b,i} \in \mathbb{R}^{c\times\tau}$ denotes $\mathbf{E}_{b,i}$ after spatial filtering; $\mathbf{W}_b \in \mathbb{R}^{c\times c}$ denotes the CSP projection matrix for the b^{th} band-pass filter; c is the number of channels; τ is the number of EEG time samples per channel; and ^{T} denotes the transpose operator.

The CSP features from $\mathbf{Z}_{b,i}$ are then given by

$$\mathbf{v}_{b,i} = \log\left(\operatorname{diag}\left(\tilde{\mathbf{W}}_b^T \mathbf{E}_{b,i}\mathbf{E}_{b,i}^T \tilde{\mathbf{W}}_b\right) / \operatorname{tr}\left[\tilde{\mathbf{W}}_b^T \mathbf{E}_{b,i}\mathbf{E}_{b,i}^T \tilde{\mathbf{W}}_b\right]\right) \tag{2}$$

where $\mathbf{v}_{b,i} \in \mathbb{R}^{1\times 2m}$; $\tilde{\mathbf{W}}_b$ represents the first m and the last m columns of which maximize the differences in the variances between 2 classes of motor imagery action; diag(·) returns the diagonal elements of a square matrix; tr[·] returns the sum of the diagonal elements in the square matrix.

Hence, the FBCSP feature vector for the i^{th} trial is represented as

$$\underset{\sim}{\mathbf{v}}_i = \left[\mathbf{v}_{1,i}, \mathbf{v}_{2,i}, \ldots, \mathbf{v}_{9,i}\right], \tag{3}$$

where $\underset{\sim}{\mathbf{v}}_i \in \mathbb{R}^{1\times(9*2m)}$.

The FBCSP feature vectors from the training data are given as

$$\bar{\mathbf{V}} = \left[\underset{\sim}{\bar{\mathbf{v}}}_1^T, \underset{\sim}{\bar{\mathbf{v}}}_2^T, \ldots, \underset{\sim}{\bar{\mathbf{v}}}_{n_t}^T\right]^T, \tag{4}$$

where $\bar{\mathbf{V}} \in \mathbb{R}^{n_t\times(9*2m)}$; $\underset{\sim}{\bar{\mathbf{v}}}_i = \left[\bar{v}_1, \bar{v}_2, \ldots, \bar{v}_{9*2m}\right] \in \mathbb{R}^{1\times(9*2m)}$ denotes the CSP feature vector from the i^{th} trial in the training data; $i = 1,\ldots,n_t$; n_t denotes the total number of trials in the training data.

C. *Mutual information- based feature selection*

The third stage performs feature selection of the extracted features using the Mutual Information-based Best Individual Features (MIBIF) algorithm [17] on the training data. This algorithm selects the best k features that results in the highest estimate of mutual information with the class labels. The corresponding CSP features which come in pairs with the selected k features are also selected. Based on the study in [8], $k = 4$ is used.

Denoting the set of features and the true class labels from the training data, $\mathbf{F} = \left[\mathbf{f}_1^T, \mathbf{f}_2^T, \ldots, \mathbf{f}_{9*2m}^T\right] = \bar{\mathbf{V}}$, where $\mathbf{f}_q^T \in \mathbb{R}^{n_t\times 1}$ is the q^{th} column vector of $\bar{\mathbf{V}}$, the mutual information between feature $\mathbf{f}_q$ with the class label class $\omega=\{1,2\}$ is given by

$$I\left(\mathbf{f}_q;\omega\right) = H\left(\omega\right) - H\left(\omega \mid \mathbf{f}_q\right) \tag{5}$$

where $H\left(\omega\right)$ and $H\left(\omega \mid \mathbf{f}_q\right)$ denotes the entropy and conditional entropy respectively. The details on the computation of these two functions are covered in [17].

After performing feature selection on $\bar{\mathbf{V}}$, the training data with selected CSP features is denoted as $\bar{\mathbf{X}}_{\text{csp}} \in \mathbb{R}^{n\times d}$ where d ranges from 4 to 8. Hence, the FBCSP feature vector for the i^{th} trial, after feature selection is performed, is represented as

$$\underset{\sim}{\mathbf{x}}_{\text{csp},i} = \left[x_{\text{csp},1,i}, x_{\text{csp},2,i}, \ldots, x_{\text{csp},d,i}\right], \tag{6}$$

where $\underset{\sim}{\mathbf{x}}_{\text{csp},i} \in \mathbb{R}^{1\times d}$.

D. *Classification*

The fourth stage performs classification using the Naïve Bayes Parzen Window (NBPW) Classifier [17] and the classification rule for two-class motor imagery is given as

$$\hat{y}_j = \underset{\omega=1,2}{\arg\max}\, p\left(\omega \mid \underset{\sim}{\mathbf{x}}_{\text{csp},j}\right), \tag{7}$$

where $\hat{y}_j$ denotes the predicted label of the j^{th} evaluation trial $\underset{\sim}{\mathbf{x}}_{\text{csp},j}$; $p\left(\omega \mid \underset{\sim}{\mathbf{x}}_{\text{csp},j}\right)$ denotes the posterior probability of the class $\omega=\{1,2\}$.

III. Phase Lock Value (PLV) Feature Extraction

The Phase Lock Value (PLV) is a measure of the synchronization in phase between two time signals [5], [14]. It ranges from 0 to 1 where 0 represents no phase synchronization and 1 represents perfect phase synchronization. The PLV feature is computed as follows:

After band-pass filtering, a common average reference (CAR) spatial filter [18] is applied on the EEG electrodes., the Hilbert transform of the EEG signal of the l^{th} EEG channel from the b^{th} band-pass filter $\mathbf{e}_{b,l}$ is computed

$$\tilde{e}_{b,l}(t) = \frac{1}{\pi} PV \int_{-\infty}^{\infty} \frac{e_{b,l}(\lambda)}{t-\lambda} d\lambda , \tag{8}$$

where PV denotes the Cauchy principal value.

The instantaneous phase is then computed as follows.

$$\Phi_{b,l}(t) = \arctan \frac{\tilde{e}_{b,l}(t)}{e_{b,l}(t)} , \tag{9}$$

The PLV between two signals at two channels denoted as channel 1 and channel 2 is given as

$$\text{PLV} = \frac{1}{\tau} \left| \sum_{t=1}^{\tau} \exp\left(j \left\{ \Phi_{b,1}(t) - \Phi_{b,2}(t) \right\} \right) \right| , \tag{10}$$

where t represents the current time sample and τ represents the total time samples. The PLV is averaged over the time samples in each single trial. Hence the PLV feature vector for the i^{th} trial is represented as

$$\underset{\sim}{\mathbf{u}}_i = \left[\mathbf{u}_{1,i}, \mathbf{u}_{2,i}, \ldots, \mathbf{u}_{9,i} \right] , \tag{11}$$

where $\underset{\sim}{\mathbf{u}}_i \in \mathbb{R}^{1\times(9*n_f)}$; $n_f = c\times(c-1)/2$ represents the number of PLV features over all channel pairs per frequency band; and c is the number of channels.

Similarly, feature selection using the MIBIF algorithm is performed on the extracted PLV features. Hence, the PLV feature vector for the i^{th} trial, after feature selection is performed, is represented as

$$\underset{\sim}{\mathbf{x}}_{\text{plv},i} = \left[x_{\text{plv},1,i}, x_{\text{plv},2,i}, \ldots, x_{\text{plv},k,i} \right] , \tag{12}$$

where $\underset{\sim}{\mathbf{x}}_{\text{plv},i} \in \mathbb{R}^{1\times k}$.

IV. PROPOSED FILTER BANK FEATURE COMBINATION (FBFC)

The proposed Filter Bank Feature Combination (FBFC) approach combines the CSP features and the PLV features. It employs a four-stage process to: first, band-pass filter the EEG using a Filter Bank; second, extract CSP and PLV features; third, perform feature combination using feature selection and feature transformation; and finally classify the transformed feature vector as shown in Fig. 2.

A. Filter Bank and Feature Extraction

The EEG data is first band-pass filtered into nine frequency components. After band-pass filtering, CSP features and PLV features are extracted from the frequency components as described in Section II and Section III.

B. Feature Combination

After feature extraction, feature selection is performed on each type of the extracted features in the training data. The MIBIF algorithm selects the best k features from each type of features that results in the highest estimate of mutual information with the class labels. Based on the results in [8], k = 4 is used for the selection of CSP features . k = 4 is also arbitrarily chosen for the selection of PLV features in this study.

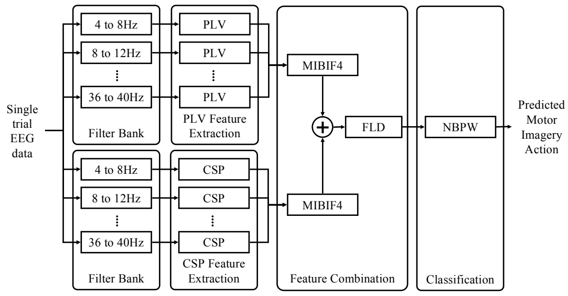

Fig. 2: Architecture of the Filter Bank Feature Combination (FBFC) approach to combine information from different types of EEG features. In this study, CSP features and PLV features are combined for two-class motor imagery EEG data. MIBIF4, FLD and NBPW represent the Mutual Information Best Individual Feature, the Fisher Linear Discriminant and the Naïve Bayes Parzen Window classifier respectively. For multi-class motor imagery, the one-versus-rest (OVR) approach is employed, where classifiers that discriminate one class against the other classes are constructed. The predicted motor imagery action depends on the maximum posterior probability output from the component classifiers.

Hence, the concatenated feature vector for the i^{th} trial is represented as

$$\underset{\sim}{\mathbf{x}}_i = \left[\underset{\sim}{\mathbf{x}}_{\text{csp},i}, \underset{\sim}{\mathbf{x}}_{\text{plv},i} \right] = \left[x_{1,i}, x_{2,i}, \ldots, x_{(d+k),i} \right] , \tag{13}$$

where d ranges from 4 to 8 in this paper, as explained in Section II.C.

Feature transformation is performed on the concatenated feature vector to reduce the feature dimension. The FBFC employs the Fisher Linear Discriminant (FLD) [19] on the concatenated feature vector $\underset{\sim}{\mathbf{x}}_i$ to form a one-dimensional feature vector for the i^{th} trial,

$$g_i = \underset{\sim}{\mathbf{x}}_i \mathbf{w}_{\text{fld}}^T , \tag{14}$$

where $\mathbf{w}_{\text{fld}} \in \mathbb{R}^{1\times(d+k)}$ is the projection vector; and $\mathbf{w}_{\text{fld}}$ maximizes the fisher criterion, a ratio of between-class to within-class variance.

C. Classification and One-Versus-Rest (OVR) approach

The FBFC employs the NBPW classifier to classify the transformed feature vector of the j^{th} evaluation trial.

$$\hat{y}_j = \underset{\omega=1,2}{\arg\max}\, p\left(\omega \mid g_j\right) , \tag{15}$$

In multi-class MI-BCI, the FBFC adopts the One-Versus-Rest (OVR) approach, where classifiers for each class of motor imagery versus all the other classes are constructed.

For a four-class MI-BCI, four OVR classifiers are required. Hence the classification rule of the NBPW classifier is thus extended from equation (15) to

$$\hat{y}_j = \underset{\omega=1,2,3,4}{\arg\max}\, p_{\text{OVR}}\left(\omega \mid g_{j,\omega}\right) , \tag{16}$$

where $p_{\text{OVR}}\left(\omega \mid g_{j,\omega}\right)$ is the probability of classifying the j^{th} evaluation trial between the motor imagery class ω and class ω' = {1, 2, 3, 4}\ ω; \ denotes the set theoretic difference operation; and $g_{j,\omega}$ represents the transformed feature vector for the ω^{th} OVR classifier.

V. EXPERIMENTAL RESULTS

The FBFC approach was evaluated on the four-class single-trial motor imagery data from the BCI Competition IV dataset IIa [10], where one training session and one evaluation session of EEG data from nine subjects are provided. Each session comprised of 288 single trials with an equal distribution of left hand, right hand, foot and tongue motor imagery. Fig. 3 shows how each trial of motor imagery is conducted. At the start of each trial, a fixation cross is displayed on the computer screen for 2s. Subsequently, a visual cue instructs the subject to perform left-hand, right-hand, foot or tongue motor imagery for 4s, followed by a break period of variable length before the next trial. To train the algorithm, the segment of 0.5s to 2.5s of EEG data after the onset of the visual cue was used. More details of the protocol are available in [10].

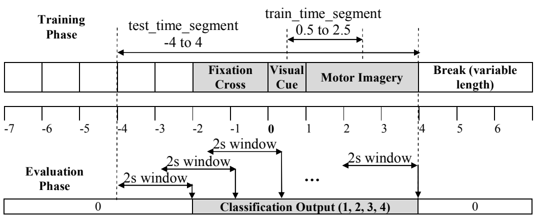

Fig. 3: The experiment protocol for a single trial of motor imagery in the four-class motor imagery data from the BCI Competition IV Dataset IIa. To train the various algorithms under study, the time segment *train_time_segment* was used. The performance of the algorithms were evaluated on the entire segment of the single trial EEG data in *test_time_segment* using sliding time windows of length *train_time_segment*

All 22 channels of EEG data were used to extract CSP features. The choice of m for the CSP algorithm in equation (2) was set to 2. This is because a greater choice of m did not significantly improve classification accuracy [6].

Only 10 out of 22 channels of EEG data, as shown in Fig. 4, were used to extract PLV features. This is to reduce the amount of processing required to extract the features. If all 22 channels of EEG data were used instead and there would be $c\times(c\text{-}1)/2 = 231$ features per frequency band, making that a total of $231\times9 = 2079$ features instead.

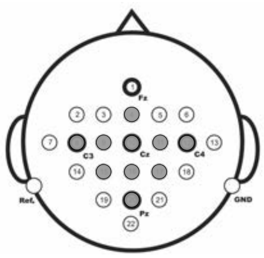

Fig. 4: PLV features were extracted from the 10 EEG channels which have been shaded in this electrode map.

A. Performance Measure

The competition performance measure used was the maximum kappa value κ, to be consistent with the performance measure employed during the BCI Competition IV. The kappa value is computed from the BIOSIG toolbox http://biosig.sourceforge.net/.

$$\kappa = \frac{p_0 - p_e}{1 - p_e}, \tag{17}$$

where p_0 denotes the classification accuracy and p_e is the chance expected agreement. Classification accuracy by chance and perfect classification would have a kappa value of 0 and 1 respectively [4]. The algorithm was evaluated on the entire single-trial EEG from the onset of the fixation cross using a sliding window of 2s.

In this study, only the data from the same subject is used to evaluate the performance of the algorithm. This is carried out in two parts. In the first part, 10 runs of 10-fold (10×10-fold) cross-validation is performed on training data. In each run, the EEG data extracted for all the 288 trials are randomly split into 10 equal portions, of which 9 portions are used as training data and the remaining portion as validation data. The maximum kappa value over 10-folds is noted. This process is then repeated for 10 runs by randomizing the manner in which the 288 trials are divided into 10 portions. The cross-validation result of the subject is then computed from the averaged kappa value of all 10 runs.

In the second part, a session-to-session transfer from the training data to the independent evaluation data is performed. The algorithm uses the EEG data from the first training session for training. The results of evaluating the algorithm on the EEG data from the second evaluation session are then presented.

B. Classification Results

The 10×10-fold cross-validations results on the training data are shown in terms of mean validation kappa value in Table I. The FBFC approach that employs both CSP features and PLV features outperforms the FBCSP algorithm that employs the CSP features only and the PLV algorithm that employs the PLV features only. Statistical analysis using the paired t-test between the FBFC and the FBCSP algorithm showed that the former performs relatively better than the other (p-value = 0.008).

The session-to-session transfer performance of the FBFC approach on the evaluation data in terms of kappa values is shown in Table II. The results of the 2nd and 3rd placed submissions in the BCI Competition IV for this dataset are also listed, and details of their methods can be found in [9]. Although not statistically significant, the FBFC approach also outperforms the FBCSP algorithm in averaged kappa value over all nine subjects.

TABLE I
KAPPA VALUE RESULTS FROM 10×10-FOLD CROSS-VALIDATIONS ON THE TRAINING DATA OF THE BCI COMPETITION DATASET IIA USING THE PROPOSED FILTER BANK FEATURE COMBINATION (FBFC), USING FILTER BANK COMMON SPATIAL PATTERN (FBCSP) AND PHASE LOCK VALUE (PLV). CLASSIFICATION ACCURACY BY CHANCE AND PERFECT CLASSIFICATION WOULD HAVE A KAPPA VALUE OF 0 AND 1 RESPECTIVELY

	10×10		
SUBJECT	FBFC	FBCSP	PLV
1	0.79	0.77	0.43
2	0.51	0.48	0.25
3	0.86	0.83	0.43
4	0.48	0.48	0.25
5	0.62	0.60	0.13
6	0.35	0.35	0.16
7	0.86	0.86	0.21
8	0.83	0.81	0.38
9	0.80	0.79	0.42
AVG	0.68	0.66	0.30

TABLE II
SESSION-TO-SESSION TRANSFER PERFORMANCE IN TERMS OF KAPPA VALUE ON THE EVALUATION DATA OF THE BCI COMPETITION IV DATASET IIA, USING THE PROPOSED FBFC AND FBCSP APPROACHES. RESULTS FROM THE 2ND AND 3RD PLACED SUBMISSION HAVE ALSO BEEN INCLUDED.

	EVALUATION			
SUBJECT	FBFC	FBCSP	2ND	3RD
1	0.79	0.80	0.69	0.38
2	0.41	0.40	0.34	0.18
3	0.81	0.76	0.71	0.48
4	0.53	0.52	0.44	0.33
5	0.35	0.37	0.16	0.07
6	0.30	0.26	0.21	0.14
7	0.76	0.79	0.66	0.29
8	0.70	0.69	0.73	0.49
9	0.69	0.63	0.69	0.44
AVG	0.59	0.58	0.52	0.31

VI. DISCUSSION AND CONCLUSION

Feature combination is an extensive area of research with applications in different areas [20]. Experimental results in studies [5], [11], [12], [14], [21] showed that feature combination yielded improved classification performance for Brain-Computer Interfaces (BCIs). Thus this paper proposed a Filter Bank Feature Combination (FBFC) approach to investigate the use of the Common Spatial Pattern (CSP) feature and the Phase Lock Value (PLV) features. The performance of the proposed FBFC is compared with the Filter Bank Common Spatial Pattern (FBCSP) algorithm that used only CSP features. The results on the four-class motor imagery data from the BCI Competition IV Dataset IIa showed that the proposed FBFC approach that combines the CSP and the PLV features outperformed the FBCSP algorithm that used only the CSP features in terms of cross-validation accuracy on the training data and session-to-session transfer on the evaluation data.

Since there are a variety of features that can be extracted from brain activity, the challenge is to investigate the effectiveness of using the proposed FBFC approach using various types of features. This could be applied in hybrid BCIs [22] or multi-modal BCIs where simultaneous measurements of brain activity such as Near Infra-red Spectroscopy (NIRS) and EEG are available. This could also be applied when features are extracted from other physiological signals such as the ECG [23]concurrently measured with EEG in hybrid BCIs. Hence, the results from the proposed FBFC motivates further investigation to use other types of features as well as other types of feature combination techniques to improve the classification performance.

ACKNOWLEDGMENT

The authors would like to thank the organizers [9] and the dataset providers of the BCI Competition IV dataset IIa [10]

REFERENCES

[1] H. H. Ehrsson, S. Geyer, and E. Naito, "Imagery of Voluntary Movement of Fingers, Toes, and Tongue Activates Corresponding Body-Part-Specific Motor Representations," *J. Neurophysiol.,* vol. 90, pp. 3304-3316, 2003.

[2] W. Penfield and T. Rasmussen, *The Cerebral Cortex of Man*. New York, N.Y: The Macmillan Company, 1950.

[3] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proc. IEEE,* vol. 89, pp. 1123-1134, 2001.

[4] A. Schlogl, F. Lee, H. Bischof, and G. Pfurtscheller, "Characterization of four-class motor imagery EEG data for the BCI-competition 2005," *J Neural Eng,* p. L14, 2005.

[5] E. Gysels and P. Celka, "Phase synchronization for the recognition of mental tasks in a brain-computer interface," *IEEE Trans. Neural Syst. Rehabil. Eng.,* vol. 12, pp. 406-415, 2004.

[6] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans Rehabil Eng,* vol. 8, pp. 441 - 446, 2000.

[7] L. Song, E. Gysels, and E. Gordon, "Phase synchrony rate for the recognition of motor imagery in brain-computer interface," in *Proc. Proc. Advances Neural Inf. Processing Systems (NIPS 05)*, 2006, pp. 1265-1272.

[8] K. K. Ang, Z. Y. Chin, H. Zhang, and C. Guan, "Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, Hong Kong, 2008, pp. 2390-2397.

[9] B. Blankertz, "BCI Competition IV," 2008.

[10] C. Brunner, M. Naeem, R. Leeb, B. Graimann, and G. Pfurtscheller, "Spatial filtering and selection of optimized components in four class motor imagery EEG data using independent components analysis," *Pattern Recogn. Lett.,* vol. 28, pp. 957-964, 2007.

[11] B. D. Mensh, J. Werfel, and H. S. Seung, "BCI competition 2003-data set Ia: combining gamma-band power with slow cortical potentials to improve single-trial classification of electroencephalographic signals," *IEEE Trans. Biomed. Eng.,* vol. 51, pp. 1052-1056, 2004.

[12] G. Dornhege, B. Blankertz, G. Curio, and K.-R. Müller, "Combining Features for BCI," in *Proc. Advances Neural Inf. Processing Systems (NIPS 02)*, 2003, pp. 1115-1122.

[13] G. Dornhege, B. Blankertz, G. Curio, and K. R. Muller, "Boosting bit rates in noninvasive EEG single-trial classifications by feature combination and multiclass paradigms," *IEEE Trans. Biomed. Eng.,* vol. 51, pp. 993-1002, 2004.

[14] C. Brunner, R. Scherer, B. Graimann, G. Supp, and G. Pfurtscheller, "Online Control of a Brain-Computer Interface Using Phase Synchronization," *IEEE Trans. Biomed. Eng.,* vol. 53, pp. 2501-2506, 2006.

[15] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. R. Müller, "Optimizing Spatial filters for Robust EEG Single-Trial Analysis," *IEEE Signal Process. Mag.,* vol. 25, pp. 41-56, 2008.

[16] G. Pfurtscheller, C. Brunner, A. Schlögl, and F. H. Lopes da Silva, "Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks," *NeuroImage,* vol. 31, pp. 153-159, 2006.

[17] K. K. Ang and C. Quek, "Rough set-based neuro-fuzzy system," in

Proc. IEEE Int. Joint Conf. Neural Netw., 2006, pp. 742-749.
[18] D. J. McFarland, L. M. McCane, S. V. David, and J. R. Wolpaw, "Spatial filter selection for EEG-based communication," *Electroencephalogr Clin Neurophysiol.,* vol. 103, pp. 386-394, Sep 1997.
[19] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, Second Edition ed.: John Wiley & Sons, Inc, 2001.
[20] J. Yang, J.-y. Yang, D. Zhang, and J.-f. Lu, "Feature fusion: parallel strategy vs. serial strategy," *Pattern Recognition,* vol. 36, pp. 1369-1381, 2003.
[21] G. Dornhege, B. Blankertz, G. Curio, and K.-R. Müller, "Increase information transfer rates in BCI by CSP extension to multi-class," in *Proc. Advances in Neural Information Processing Systems*, 2004, pp. 733-740.
[22] G. Pfurtscheller, B. Z. Allison, G. Bauernfeind, C. Brunner, T. Solis Escalante, R. Scherer, et al., "The hybrid BCI," *Frontiers in Neuroscience,* vol. 5, p. 5, 2010-April-21 2010.
[23] G. Pfurtscheller, R. Leeb, D. Friedman, and M. Slater, "Centrally controlled heart rate changes during mental practice in immersive virtual environment: A case study with a tetraplegic," *Int. J. Psychophysiol.,* vol. 68, pp. 1-5, 2008.