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Multiclass Voluntary Facial Expression Classification based on Filter Bank Common Spatial Pattern

Zheng Yang Chin, Kai Keng Ang, Cuntai Guan

Abstract—**This paper investigates the classification of voluntary facial expressions from electroencephalogram (EEG) and electromyogram (EMG) signals using the Filter Bank Common Spatial Pattern (FBCSP) algorithm. The FBCSP algorithm is an autonomous and effective machine learning approach for classifying two classes of EEG measurements in motor imagery-based Brain Computer Interface (BCI). However, the problem of facial expression recognition typically involves more than just two classes of measurements. Hence, this paper proposes an extension of FBCSP to the multiclass paradigm using a decision threshold-based classifier for classifying facial expressions from EEG and EMG measurements. A study is conducted using the proposed Multiclass FBCSP on 4 subjects who performed 6 different facial expressions. The results show that the Multiclass FBCSP is effective in classifying multiple facial expressions from the EEG and EMG measurements.**

I. Introduction

Brain signals can be acquired by scalp-recorded electroencephalogram (EEG) non-invasively from a subject. Over the past 20 years, EEG and other brain signals have been applied in augmentatative communication and control technology for those with severe neuromuscular disorders such as amyotrophic lateral sclerosis and stroke [1]. In a Brain-Computer Interface (BCI), these brain signals are directly translated into commands for controlling an external device[1]. Recently, increased research efforts have widen the potential applications of decoding these brain signals for gaming, digital entertainment [2], as well as post-stroke rehabilitation [3].

This paper extends the translation of EEG and electromyogram (EMG) measurements to the recognition of facial expressions. Facial expressions are an effective communication means for people to convey emotions [4]. For example, stroke patients suffer facial paralysis because neurological damages affect regions of the brain that are involved in the production and regulation of these facial expressions [5]. Restoring the capability of facial expressions for these patients is important because depression symptoms have been reported in 65% of patients with facial neuromotor disorders, an incidence that is 3 to 5 times higher than the general population [4]. Due to the neuroplasticity nature of the brain, neuromuscular facial retraining techniques [6] used with EMG biofeedback can help improve the patients' facial functions [7]. In another example, facial expressions elicited from the user can be used to control a virtual avatar in a computer game (http://www.emotiv.com) or used to evaluate how immersive the game is [8]. Thus, the effective recognition of multiple facial expressions using EEG and EMG measurements has a strong potential for facial function rehabilitation as well as digital entertainment.

The Common Spatial Pattern (CSP) algorithm was first introduced into the field of EEG analysis to classify abnormal from normal EEG, to extract the components from abnormal EEG, and to localize the sources [9]. It is also highly effective in constructing optimal spatial filters for discriminating two classes of EEG measurements in a motor imagery-based BCI [10]. However, the effectiveness of the CSP algorithm is highly dependent on the operational frequency band due to the huge inter-subject variability of the brain signals [11]. To address this issue, the Filter Bank Common Spatial Pattern (FBCSP) algorithm [12] is developed to perform autonomous selection of key temporal-spatial discriminative EEG characteristics. However, the application of FBCSP is still limited to two classes of EEG measurements. Moreover, the problem of facial expression recognition typically involves more than two types of facial expressions. Therefore, an extension of the FBCSP algorithm to the multiclass paradigm using a decision threshold-based classifier is proposed in this paper.

The remainder of this paper is organized as follows. Section II provides a brief description of the CSP and FBCSP algorithms used in this paper. Section III describes the classifier used in FBCSP. Section IV presents the proposed multiclass extension to FBCSP using a decision threshold-based classifier. Section V describes the experimental protocol of the study and section presents the results. Section VI concludes this paper with a discussion on the results.

II. Filter Bank Common Spatial Pattern (FBCSP)

The *Common Spatial Pattern* (CSP) algorithm is highly successful in computing spatial filters for EEG measurements. The objective of spatial filtering employing the CSP algorithm is to compute the features whose variances are optimal for discriminating two classes of EEG

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Z. Y. Chin, K. K. Ang and C. Guan are with Institute for Infocomm Research, Agency for Science, Technology and Research (A*STAR), 21 Heng Mui Keng Terrace, Singapore 119613. (email: {zychin, kkang, ctguan }@i2r.a-star.edu.sg).

measurements.

The method employed by the CSP algorithm is based on the simultaneous diagonalization of two covariance matrices. In summary, the spatially filtered signal $\mathbf{Z}$ of a single trial EEG $\mathbf{E}$ is given as

$$\mathbf{Z} = \mathbf{WE}. \tag{1}$$

where $\mathbf{E}$ is an $N \times T$ matrix of EEG data for a single trial; N is the number of channels; T is the number of measurement samples per channel; and $\mathbf{W}$ is the CSP projection matrix. The rows of $\mathbf{W}$ are the stationary spatial filters and the columns of $\mathbf{W}^{-1}$ are the common spatial patterns.

The spatial filtered signal $\mathbf{Z}$ given in (1) maximizes the differences in the variance of the two classes of EEG measurements. However, the variances of only a small number m of the spatial filtered signal are generally used as features for classification [10] . The m first and last rows of $\mathbf{Z}$ i.e. $\mathbf{Z}_p$, $p \in \{1..2m\}$ form the feature vector X_p given in (2) as inputs to a classifier.

$$X_p = \log\left(\operatorname{var}\left(\mathbf{Z}_p\right) \Big/ \sum_{i=1}^{2m} \operatorname{var}\left(\mathbf{Z}_i\right)\right) \tag{2}$$

To address the problem of selecting the operational subject-specific frequency band for the CSP algorithm, the FBCSP algorithm [12] is developed. The architecture of FBCSP is shown in Fig. 1.

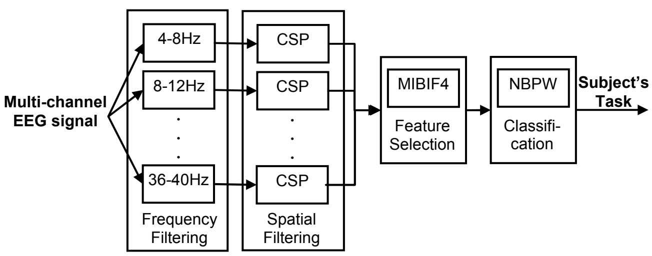

Fig. 1. Architecture of the FBCSP algorithm adapted from [12]

FBCSP comprises four stages: frequency filtering, spatial filtering, feature selection and classification. The first stage employs a zero-phase Chebyshev II filter bank that bandpass filters the EEG measurements into multiple bands. The second stage performs spatial filtering on each of these bands using the CSP algorithm. Thus, each pair of bandpass and spatial filter yields CSP features that are specific to the frequency range of the bandpass filter. The third stage employs a feature selection algorithm to select the discriminative CSP features from the filter bank. The fourth stage employs a classification algorithm to model and classify the selected CSP features. These four stages of EEG signal processing perform an autonomous selection of key temporal-spatial discriminative EEG characteristics using a machine learning approach. In this paper, the Mutual Information Best Individual Feature (MIBIF) algorithm and the Naïve Bayes Parzen Window (NBPW) [12] are used to select and classify the multiband CSP features respectively.

III. Naïve Bayes Parzen Window

The *Naïve Bayesian Parzen Window* (NBPW) classifier [13] estimates $p(\mathbf{X}|\omega)$ and $P(\omega)$ from training data samples and predicts the class ω with the highest posterior probability $p(\omega|\mathbf{X})$ using Bayes rule

$$p(\omega \mid \mathbf{X}) = p(\mathbf{X} \mid \omega) P(\omega) / p(\mathbf{X}), \tag{3}$$

where $\mathbf{X}=\{X_1,X_2,\ldots,X_d\}$ is a data sample with d features. The computation of $p(\omega|\mathbf{X})$ is rendered feasible by a naïve assumption that all the features $X_1,X_2,\ldots,X_d$ are conditionally independent given class ω in

$$p(\mathbf{X} \mid \omega) = \prod_{i=1}^{d} p(X_i \mid \omega). \tag{4}$$

The NBPW classifier employs Parzen Window to estimate the conditional probability $p(X_i|\omega)$

$$\hat{p}(X_i \mid \omega) = \frac{1}{n_\omega} \sum_{j \in I_\omega} \phi\left(X_i - X_{i,j}, h\right), \tag{5}$$

where $\omega=1,\ldots,N_\omega$; n_ω is the number of data samples belonging to class ω; I_ω is the set of indices of the data samples belonging to class ω; and ϕ is a smoothing kernel function with a smoothing parameter h [13].

IV. Multiclass FBCSP

The CSP algorithm employed in FBCSP computes optimal features for binary classification [9]. However, for multiclass classification, there is no canonical method in computing the relevant CSP patterns [14]. Several approaches have been proposed to extend the CSP algorithm to multiclass paradigm, namely, using CSP *within the classifier*, *One Versus the Rest* CSP (OVR), and *simultaneous diagonalization* [9],[14]. The proposed Multiclass FBCSP algorithm employs a *divide-and-conquer* approach that is similar to OVR whereby the multiclass problem is reduced into a series of binary classifiers. This divide-and-conquer approach is described as follows:

A. Divide-and-Conquer approach

Given C classes, construct C-1 binary classifiers. The classification rule for the k^{th} classifier is given by

$$\begin{aligned} &\text{decide } \omega_k \text{ if } \left(p(\omega_k \mid \mathbf{X}) > p(\omega_{k'} \mid \mathbf{X})\right) \mid (k' > k) \\ &\text{else } k \rightarrow k+1 \end{aligned} \tag{6}$$

where $k,k' \in \Omega$; $\Omega \in \{1,2...,C\}$; and $p(\omega_{k'} \mid \mathbf{X}) = 0$ if $k' = \varnothing$.

This approach computes CSP features to discriminate class ω_k from $\omega_{k'}$. This approach is employed instead of using pair wise classifiers because fewer patterns are chosen and no advantage was observed in the latter [14]. In this approach, the design of the first classifier is critical because the errors that propagate to the subsequent (C-1-k) classifiers will impact the overall classification accuracy. A method of determining which class of data to classify first can be performed using the *one-against-all* cross-validation accuracies whereby ω_k is classified against the others.

B. Decision threshold-based Classification

This paper investigates whether classification accuracies can be improved in the Multiclass FBCSP algorithm with decision threshold-based classifiers. A decision threshold-based classifier compares the classifier estimates of the posterior probabilities with a specified threshold [15]. For a binary classifier,

$$\text{decide } \omega_1 \text{ if } \frac{p(\omega_1 \mid \mathbf{X})}{p(\omega_1 \mid \mathbf{X}) + p(\omega_2 \mid \mathbf{X})} \geq t; \quad \text{otherwise decide } \omega_2 \tag{7}$$

where t is a constant value for the threshold between 0 and 1

Without varying the decision thresholds, t = 0.5 by default. The thresholds are computed in the following steps:

- Step 1: Set all the decision thresholds to 0.5

$$t_k = 0.5 \tag{8}$$

where $k = 1, \ldots, C-1$

- Step 2: k = 1, Assign t_k to i if

$$g(i) > g(j) \text{ for all } j \neq i \tag{9}$$

where $i, j \in \{0.5 : 0.05 : 0.95\}$ and g(i) is the training set accuracy with threshold i from 10×10-fold cross-validation results of the Multiclass FBCSP. This is to avoid a biased selection of t_k

- Step 3: $k \rightarrow k$+1, repeat Step 2 until $k = C$ - 1

V. EXPERIMENTAL RESULTS

4 healthy subjects were recruited for this study. The data is collected with approval from the Ethics Approval Board. 360 trials of EEG/EMG data were recorded using Neuroscan NuAmps 40-channel Quik-Cap. Each subject performed 6 types of facial expressions: *Smile*, *Straight*, *Wince*, *Agape*, *Stern* and *Frown*. These expressions are performed similar to the experiment performed in [16]. These facial expressions typically convey happy, calm, disgust, shock, angry and sad respectively. In [17], being happy is neither necessary nor sufficient for smiling. Thus the former group of names is used instead of the latter to emphasize the physical imitation of facial expressions rather than emotions. Fig. 2 shows the visual cues presented to the subjects.

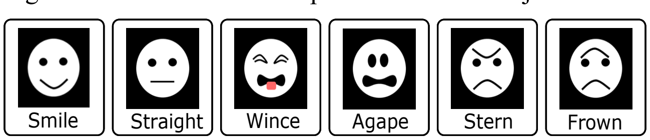

Fig. 2. Visual cues for the facial expressions exhibited during the data collection. Each trial begins with a 2s preparation period where a fixation cross appears on a computer screen. Next, the visual cue instructs the subject to perform the facial expression for 4s. Finally, the subject rests for 4s in preparation for the next trial.

Current literature suggests that a subject takes about 0.5s to mimic the facial expression seen in static images [18]. Thus, the EEG/EMG data of 0.5 to 2.5 seconds from the onset of the visual cue for each trial is analyzed by extracting the feature vectors given in (2). The EEG/EMG data is extracted from 34 electrodes, namely, Fp1, Fp2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, O1, Oz, O2, FT9, FT10, PO1, and PO2. These 34 electrodes record both EEG and EMG data simultaneously.

The order of classification in the Multiclass FBCSP algorithm is determined from the *one-against-all* 10×10-fold cross-validation accuracies. *Smile* is classified first, followed by *Straight*, *Wince*, *Agape*, *Stern* and finally *Frown*. Fig. 3 shows the results of unbiased 10×10-fold cross-validations performed using the Multiclass FBCSP. The results from 34 electrodes yield a test accuracy of 86.0±0.80%.

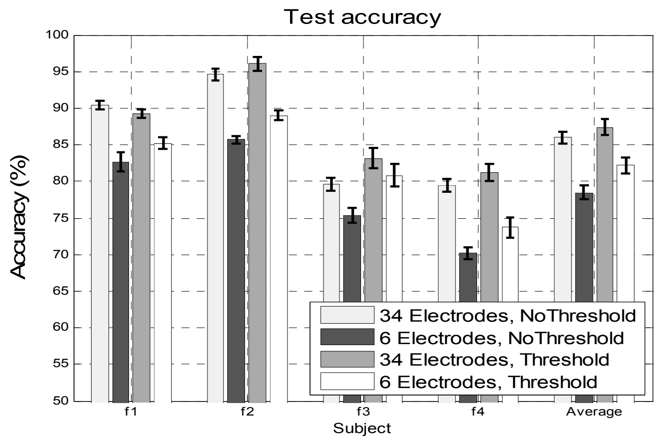

Fig. 3. Experimental results of using the proposed Multiclass FBCSP algorithm for 4 subjects performing 6 facial expressions. The vertical bars show the test accuracies of 10×10-fold cross-validations performed using the proposed Multiclass FBCSP on the EEG/ EMG measurements. The vertical lines show the standard deviations of the test accuracies. Results are obtained using EEG/EMG measurements from 34 electrodes and 6 frontal electrodes. 'NoThreshold' and 'Threshold' results are obtained without using and with using decision threshold-based classification respectively.

As a reduced set of electrodes is desired for a headband implementation of the BCI, the results from 6 frontal electrodes (Fp1, Fp2, F7, F8, FT9 and FT10) are also presented in Fig. 3. The results yield a significant decrease in accuracy from 86.0±0.80% to 78.5±0.91% (p-value from paired samples t-test = 0.0072). These results are significant because humans can discern 6 basic facial expressions with an accuracy of 70% to 98%, and image/video-based detection systems achieve an accuracy of 64% to 98% from classifying 3 to 7 facial expressions by 5 to 40 subjects [19].

The results for the decision threshold based-classifiers are also shown in Fig. 3. The results from 6 electrodes yield a significant improvement from 78.5±0.91% to 81.8±0.87% (p-value = 0.0096). The results from 34 electrodes yield a marginal improvement from 86.00±0.80% to 87.1±0.76% (p-value = 0.1096). Table 1 shows the confusion matrices of the cross-validations accuracy for 34 electrodes and compares between with and without the decision threshold-based classifiers. Although the classification accuracy of *Smile* is decreased slightly from 97.42% to 93.54%, the classification accuracies of *Stern* and *Frown* show significant improvement from 83.21% to 88.71% and from 66.71% to 77.29% respectively when the decision threshold-based classifiers are employed.

TABLE I

THE CONFUSION MATRICES AVERAGED OVER FOUR SUBJECTS, USING 34 ELECTRODES WITH DECISION THRESHOLDS AND WITHOUT DECISION THRESHOLDS. THE MEAN ACCURACY RESULTS FOR THE 10X10-FOLD CROSS VALIDATION ACCURACIES FOR EACH CLASS IS SHOWN.

		Predicted Class											
		With Varying Decision Threshold						Without Varying Decision Threshold					
		Smile	Straight	Wince	Agape	Stern	Frown	Smile	Straight	Wince	Agape	Stern	Frown
True Class	Smile	93.54	0.75	0.71	4.29	0.04	0.67	97.42	0.96	0.17	1.04	0.00	0.42
	Straight	0.96	92.54	0.00	0.13	2.67	3.71	2.33	93.67	0.00	0.00	1.46	2.54
	Wince	4.63	0.54	84.38	3.08	2.83	4.54	5.54	0.75	85.63	2.83	1.83	3.42
	Agape	3.54	0.08	0.50	88.04	1.38	6.46	6.92	0.08	0.21	89.38	1.33	2.08
	Stern	0.00	2.67	3.67	1.21	88.71	3.75	0.04	5.00	7.00	1.29	83.21	3.46
	Frown	0.38	5.63	4.00	8.04	4.67	77.29	1.04	6.83	10.17	10.88	4.38	66.71

VI. CONCLUSIONS

This paper investigates the classification of 6 different facial expressions using EEG and EMG measurements via a proposed extension of the Filter Bank Common Spatial Patterns (FBCSP) algorithm to the multiclass paradigm. The study is performed on 4 healthy subjects. The results show the Multiclass FBCSP effectively classifies 6 different facial expressions from EEG and EMG measurements. The results also demonstrate an improvement in the accuracy of the Multiclass FBCSP using the decision threshold-based classifier.

The classification accuracy of the proposed Multiclass FBCSP on a reduced set of electrodes from 34 to 6 is also investigated. The result from using 6 frontal electrodes yields a significant decrease in accuracy compared against 34 electrodes. From the concept of the human homunculus [5],[20], there is a motor representation of the face in the motor cortex. Evidence in the literature using functional Magnetic Resonance Imaging (fMRI) also show that the premotor cortex is activated during voluntary imitation [21],[22] or imagination [23] of facial expressions. The decrease in accuracy result suggests that there are relevant signals from the premotor cortex and motor cortex related to the imitation of voluntary facial expressions. Future research works include an optimization of the number and placement of electrodes, and a more extensive study into the performance of combining classifiers in the multiclass paradigm.

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