ICA+OPCA FOR ARTIFACT-ROBUST CLASSIFICATION OF EEG DATA

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Abstract. EEG-based brain computer interface (BCI) provides a new communication channel between human brain and computer. An important task in an EEG-based BCI system is to analyze EEG patterns. EEG data is a multivariate time series, so hidden Markov model (HMM) might be a good choice for classification. However EEG is very noisy data and contains artifacts, thus the extraction of features that are robust to noise and artifacts is important. In this paper we present a method which employ both independent component analysis (ICA) and oriented principal component analysis (OPCA) for artifact-robust feature extraction. The high performance of our method is confirmed by experimental study on classifying EEG into 4 categories which consist of left/right/up/down movements during imagination.

INTRODUCTION

Brain computer interface (BCI) is a system which translates a subject's intentions into a control signal for a device, e.g., a computer application, a wheelchair or a neuroprosthesis [12]. BCI provides a new communication channel between human brains and computers and adds a new dimension to human computer interface (HCI). It was motivated by the hope of creating new communication channels for disabled persons, but recently draws attention in multimedia communication [4]. In this paper pay our attention to an EEG-based BCI system, thus, EEG pattern analysis is critical.

Several attempts have been made for EEG pattern recognition in which general consists of two procedures: (1) feature extraction; (2) classification. Various feature extraction methods were used. These include adaptive autoregressive (AAR) model, Hjorth parameters [10], power spectrum, and principal component features [8, 9]. For classification, linear discriminant analysis (LDA), artificial neural networks, linear dynamical systems (a.k.a

Kalman filter) [8], and HMM [10, 11] were employed.

One of main difficulties in analyzing EEG patterns, lies in the fact that EEG data contain various artifacts such as ocular artifact and muscle artifact. This is an important problem, and many researchers usually have rejected artifacts including trials to get clean EEG data. ICA was shown to be useful in removing these artifacts [7]. ICA finds a nonorthogonal linear transform with basis coefficients being statistically independent (see [6] and references therein). If the underlying generation process obeys the linear model where the observed signals are linear mixtures of statistically independent latent variables (sources), then these unknown sources can be recovered without resorting to any prior knowledge of the mixing matrix. This is known as blind source separation (see [2] and references therein).

On the other hand, PCA is a well-known classical method for dimensionality reduction. It finds directions which retain maximum variance in lower dimensional space. In the task of EEG pattern recognition, principal component features were shown to useful [8, 9]. However principal component directions do not consider the effect of artifacts because these directions rely on only signal subspace. OPCA is an extension of PCA which is able to find steered directions, depending on noise distribution [3]. In fact OPCA aims at finding directions which maximize the ratio of signal covariance to noise covariance. Hence principal oriented components are expected to produce artifact-robust features, in contrast to principal component features.

In this paper we present a method which exploits principal oriented component features for artifact-robust EEG pattern recognition. Since OPCA requires the noise covariance which is not available in advance, we extract artifacts by ICA and regenerate noisy data from these extracted artifacts only. The principal oriented component features are used to train HMMs for classification. The high performance of our method is confirmed by experimental study on classifying EEG data into 4 categories which consist of left/right/up/down movements during imagination.

OPCA

PCA aims to find a linear orthogonal transformation $\boldsymbol{y} = \boldsymbol{W}\boldsymbol{x}$ (where $\boldsymbol{x}$ is the observation vector) such that the retained variance is maximized. Alternatively, PCA is viewed as a minimizer of reconstruction error. It turned out that these principles (variance maximizer or reconstruction error minimizer) leads to a symmetric eigenvalue problem. The row vectors of $\boldsymbol{W}$ correspond to the normalized orthogonal eigenvectors of the data covariance matrix.

OPCA is an extension of the conventional PCA. In the presence of undesirable subspaces (for example artifact subspaces), OPCA searches for an optimal solution oriented toward the directions where the unwanted direction has minimum energy while maximizing the projection energy of input signal [3]. In fact OPCA finds a direction which maximize the generalized Rayleigh quotient for the matrix pencil $(\boldsymbol{R}_x, \boldsymbol{R}_v)$ where $\boldsymbol{R}_x$ is the covariance matrix of the signal and $\boldsymbol{R}_v$ is the covariance matrix of the noise (unwanted signal). Thus it corresponds to the symmetric generalized eigenvalue problem.

The objective function for OPCA is given by the signal-to-signal ratio (SSR) between two random vectors $\boldsymbol{x}$ and $\boldsymbol{v}$:

$$\mathcal{J}_{OPCA}(\boldsymbol{w}) = \frac{E\left\{\boldsymbol{w}^T\boldsymbol{x}\right\}^2}{E\left\{\boldsymbol{w}^T\boldsymbol{v}\right\}^2} = \frac{\boldsymbol{w}^T\boldsymbol{R}_x\boldsymbol{w}}{\boldsymbol{w}^T\boldsymbol{R}_v\boldsymbol{w}}. \tag{1}$$

The objective function (1) is nothing but a generalized Rayleigh quotient. A solution which maximizes (1) corresponds to the largest generalized eigenvector of the matrix pencil $(\boldsymbol{R}_x, \boldsymbol{R}_v)$. Note that $\boldsymbol{R}_v$ is assumed to be positive definite. The direction $\boldsymbol{w}$ is steered by the distribution of $\boldsymbol{v}$, in contrast to PCA. When the random vector $\boldsymbol{v}$ has isotropic distribution, OPCA becomes the ordinary PCA.

METHODS

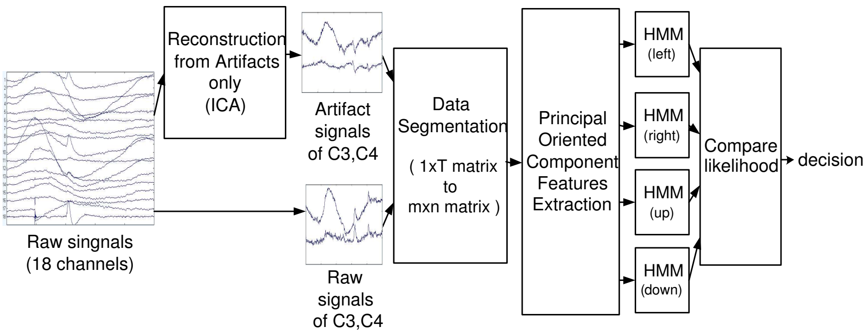

Figure 1: A schematic diagram for our proposed method.

We consider mainly C3 and C4 channels located in sensorimotor cortex related with (imagery) movements. Fig. 1 shows a schematic diagram for our proposed method. First we extract artifacts by ICA. These extracted artifacts are used to reconstruct unwanted signals which are required in OPCA. Data segmentation converts a time series into a multivariate signal so that OPCA can be applied. Principal oriented component features are fed into HMMs which are our classifiers. Depending on the log-likelihood values, an appropriate class (left/right/up/down) is determined.

Data Acquisition

We designed eight different visual stimuli which help a subject to imagine some particular movement easily. All these stimuli were designed to facilitate the task of imagination, which is concerned with the movement toward one of 4 directions (left/right/up/down). Fig. 2 shows exemplary pictures for eight different stimuli:

(1) *stick (s)*: let the stick fall down
(2) *alphabet (a)*: move a letter to the inside of a circle
(3) *rope (r)*: throw a rope over a stick
(4) *wall (w)*: push a wall
(5) *egg (e)*: stretch one hand out for an egg not to fall to the ground
(6) *button (b)*: click a confirm button
(7) *puzzle (p)*: carry out a picture puzzle
(8) *mouse (m)*: dig a tunnel through a mountain.

For each stimulus, a subject undergoes 3 sessions (1 session = 2 runs = 40 trials) which consist of: (1) use one dominant hand in imagery movement; (2) use both hands in imagery movement; (3) use both hands as well as speak an associated word (in his/her mind) simultaneously. The protocol of a session is shown in Fig. 3. Fig. 3 shows brief timing structure and detail timing diagram of each stimuli for one trial. A monitor shows stimuli during the cue terms or the fall(stick and egg) terms, and subjects imagine hands moving during the imagination term.

EEG signals were recorded from 20 electrodes, 17 of which were placed according to the international 10-20 system but two channels(Fz and Pz) were omitted for the sake of simplicity. Two ground electrodes were glued to ears. The other electrode was used for recording the EOG channel. Data were sampled at 200Hz rate and were preprocessed by a bandpass filter with a frequency range between 0.1 and 35Hz.

Feature Extraction: ICA+OPCA

Ocular artifact (caused by eye movement/blinking) and muscle artifact are exemplary unwanted signals which severely influence evoked responses in an unsuitable way. These artifacts could be minimized by simply asking a subject to avoid eye movement/blinking as much as possible. However a subject's concentration on not moving his/her eyes results in a secondary task which might disturb the experimental protocol. A more reasonable way is to discard the trials which are contaminated by artifacts. This can be done by recording EOG signals. However we might lose some useful information by throwing away the portion of contaminated signals. For example, if a subject is a disabled person who has sporadic muscle activity, then most of EEG data are contaminated by artifacts. Thus, it is desirable to exploit features which are robust to artifacts, which is our main interest in this paper. This section describes how we extract artifact-robust features by using ICA and OPCA.

Generation of Unwanted Signals by ICA.
ICA was applied in EEG data analysis and was shown to be successful in suppressing artifacts. Its usefulness is based on two plausible premises: (1) EEG data recorded at multiple scalp sensors are linear sums of temporally independent components arising from spatially fixed, distinct or overlapping

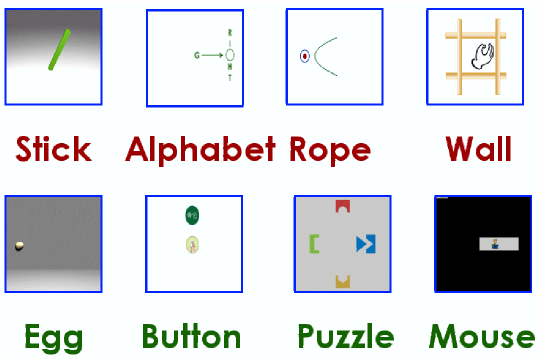

Figure 2: Exemplary pictures for visual stimuli.

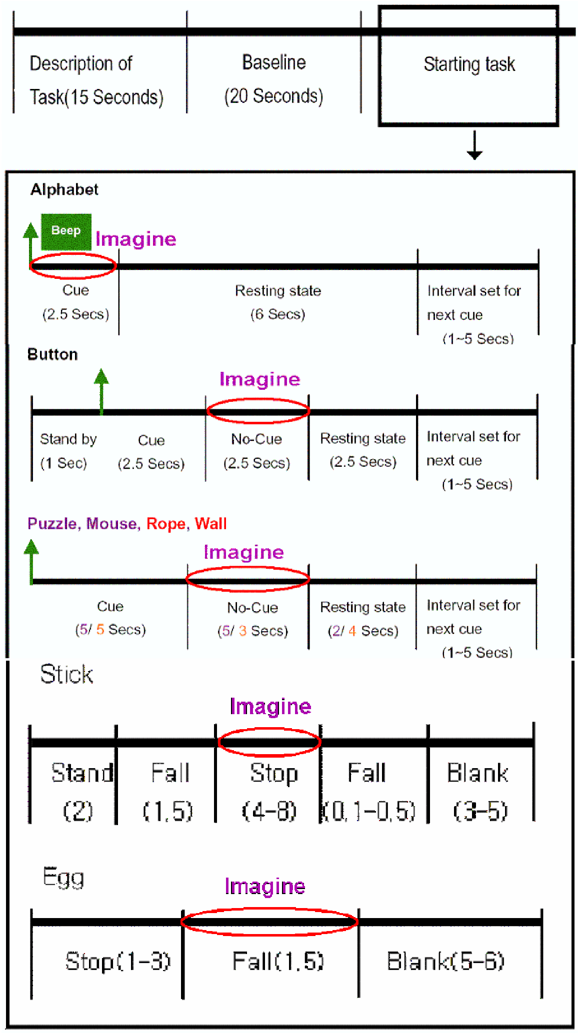

Figure 3: Protocol of session.

brain or extra-brain networks; (2) the spatial spread of electric current from sources by volume conduction does not involve significant time delays [7].

Given a set of measured EEG data denoted by $\boldsymbol{X} = [\boldsymbol{x}_1, \ldots, \boldsymbol{x}_N]$, ICA finds a linear transformation $\boldsymbol{B}$ such that each column vector of $\boldsymbol{Y} = \boldsymbol{BX}$ consists of statistically independent components. Some components in $\boldsymbol{y}_t$ correspond to artifacts and noise, so their contribution can be eliminated by an inverse mapping $\boldsymbol{B}^{-1}$ with setting the rows in $\boldsymbol{Y}$ corresponding to artifacts to zeros.

In contrast, we keep only artifact components and reconstruct the data by an inverse mapping $\boldsymbol{V} = \boldsymbol{B}^{-1}\boldsymbol{Y}$ with setting the rows in $\boldsymbol{Y}$ corresponding to non-artifact components to zeros. In this way we construct unwanted signals which will be used in OPCA.

In order to automatically detect artifact components in ICA, we use the EOG signal. The detection is carried out by investigating the difference between the normalized magnitude of the EOG signal and the independent component signals. Alternatively correlations between the EOG signal and the independent component signals can be considered to detect ocular artifact components. In general, muscle artifact signals have large variance. Hence we sort independent components in a descending order according to their variances, then we treat first several components to be artifacts. In this way, we extract artifacts by ICA in an automatic fashion. Thus unwanted signals $\boldsymbol{V}$ are reconstructed. Any ICA algorithms can be used. In this paper we use the flexible ICA algorithm which exploits the generalized Gaussian density model and the natural gradient in Stiefel manifold [1].

Principal Oriented Component Features.
We consider the rows in both data matrix $\boldsymbol{X}$ and the unwanted signal matrix $\boldsymbol{V}$, which correspond to C_3 and C_4 channels. Each row is a time series data and we decompose it into K overlapping blocks to construct an $M \times K$ data matrix where M is the number of data points in each block (see Fig. 4). This data segmentation produces $\boldsymbol{X}_{raw}^{C_3} \in \mathbb{R}^{M\times K}$ and $\boldsymbol{X}_{noise}^{C_3} \in \mathbb{R}^{M\times K}$. For the C_4 channel, the same process is undergone to construct $\boldsymbol{X}_{raw}^{C_4}$ and $\boldsymbol{X}_{noise}^{C_4}$.

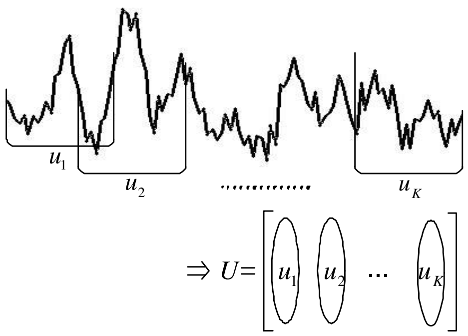

Figure 4: Data segmentation which converts a time series data into a data matrix.

For the sake of simplicity we omit indices C_3 and C_4 because the same processing is carried out for both channels, separately. The OPCA considers two correlation matrices, $\boldsymbol{R}_{raw} = \boldsymbol{X}_{raw}\boldsymbol{X}_{raw}^T$ and $\boldsymbol{R}_{noise} = \boldsymbol{X}_{noise}\boldsymbol{X}_{noise}^T$, and solves a generalized eigenvalue problem:

$$\boldsymbol{R}_{raw}\boldsymbol{W} = \boldsymbol{R}_{noise}\boldsymbol{\Lambda}\boldsymbol{W}. \tag{2}$$

The row vectors of $\boldsymbol{W}$ correspond to principal oriented component directions. We compute OPCA transforms for 4 different categories and two channels (C_3 and C_4), which lead to eight different transformation matrices, $\boldsymbol{W}_{C_i,L}$, $\boldsymbol{W}_{C_i,R}$, $\boldsymbol{W}_{C_i,U}$, $\boldsymbol{W}_{C_i,D}$, $i = 3, 4$ (L, R, U *and* D correspond to left/right/up/down movement, respectively). Exemplary OPCA basis functions are shown in Fig. 5.

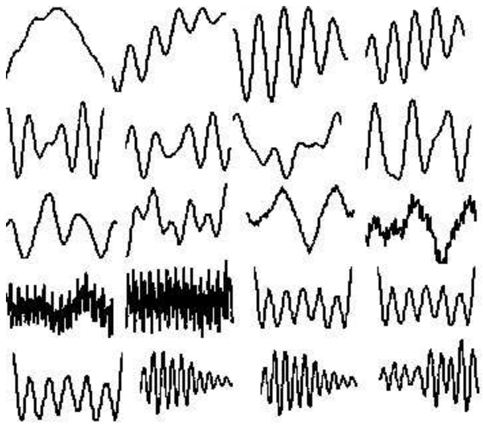

Figure 5: Exemplary OPCA basis functions.

Classification by HMMs

Principal oriented component features corresponding to C_3 and C_4 channels (for each category) are concatenated, then, are fed into continuous HMMs (HMM_L, HMM_R, HMM_U and HMM_D) in the training phase. Given a set of features for a test EEG signal, it is assigned to a class having the largest log-likelihood value. Since HMM is a well-known method, details are left out (see [5] for review of HMMs).

EXPERIMENTAL RESULTS

In order to show the robustness of OPCA features, we compare our method with the PCA-based method [9] where principal component features were shown to outperform AAR features, Hjorth parameters, and raw data.

Experimental results are summarized in Tables 1 and 2. For each run of

Table 1: The comparison of classification performance (mean accuracy) between our method (ICA+OPCA) and the PCA-based method (PCA) for 8 different data sets: S (stick); A (alphabet); R (rope); W (wall); E (egg); B (button); P (puzzle); M (mouse). The percent correct classification is computed by averaging 3 sessions: dominant hand (DH); both hands (BH); both hands with language (BHL).

Method	Types of visual stimuli							
	S	A	R	W	E	B	P	M
ICA+OPCA	95.83	92.75	90.67	94.75	99.26	99.17	89.19	91.75
PCA	79.67	85.17	88.50	76.75	98.37	82.25	80.37	79.92

Table 2: The comparison of classification performance (mean accuracy) for each session. The percent correct classification is averaged over 8 different visual stimuli.

Method	DH	BH	BHL	Average
ICA+OPCA	92.53	95.00	94.98	94.17
PCA	79.35	84.89	87.39	83.87

simulation, we calculated the mean of 5-fold cross validation and simulations were repeated 50 times to compute the mean accuracy.

Figs. 6 and 7 show the rectangular box plots of two methods: (1) left-half is for our proposed method (ICA+OPCA); (2) right-half is for the PCA-based method. The box has lines at the lower quartile, median, and upper quartile values. The whiskers are lines extending from each end of the box to show the extent of the rest of the data. Compared to the PCA-based method, the proposed method has higher accuracy as well as higher reliability (variations between upper and lower bounds are much smaller). The proposed method gives average performance around 95%, whereas the PCA-based method is around 84%.

In Fig. 7, one can observe that the result for BH session is better than DH session and BHL session. At this moment, we do not have a clear idea why BH session gives us the best classification performance. Using both hands in imagination could help the subject to concentrate more on the experiment than using either dominant hand or both hands with language. This will require more investigation in a view point of cognitive science.

CONCLUSION

In this paper we have presented a method of jointly employing ICA and OPCA for extracting artifact-robust features. Artifacts extracted by ICA were used to re-generate unwanted signals which are necessary in performing OPCA. Our extensive experiments confirmed the high performance of our method (ICA+OPCA), compared to the PCA-based method that was shown to be better than other features-based methods.

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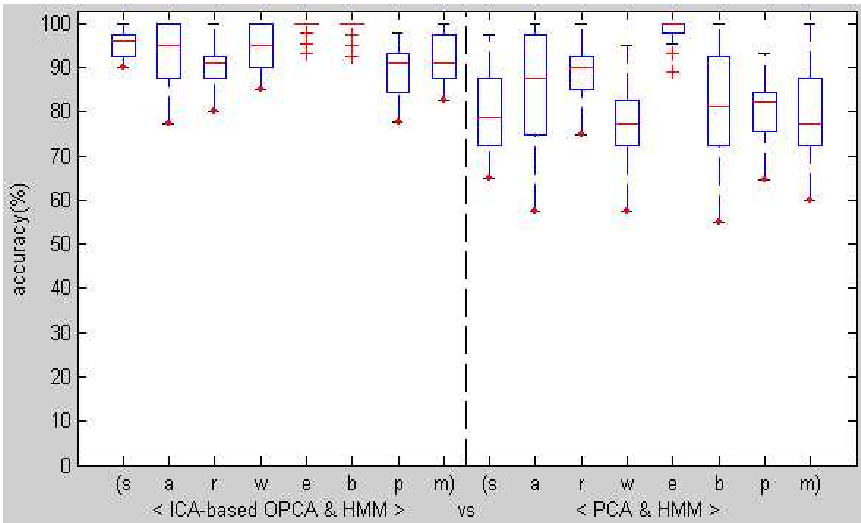

Figure 6: Classification performance of the proposed method (left-half) and of the PCA-based method (right-half) for 8 different data sets: S (stick); A (alphabet); R (rope); W (wall); E (egg); B (button); P (puzzle); M (mouse). A set of data for each stimulus contains three sessions (DH, BH, BHL).

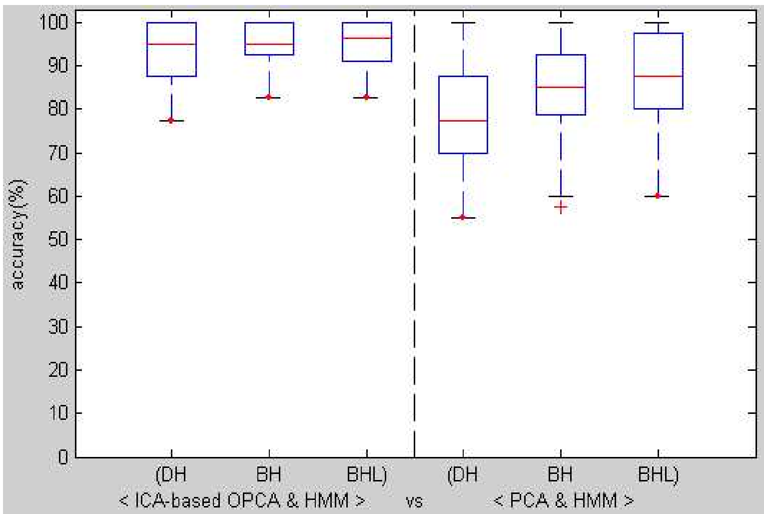

Figure 7: Classification performance of the proposed method (left-half) and of the PCA-based method (right-half) for each session. A set of data for each session contains 8 stimuli.