ICA+OPCA를 이용한 잡음에 강인한 뇌파 분류

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ICA+OPCA for Artifact-Robust Classification of EEG

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Abstract

Electroencephalogram (EEG)-based brain computer interface (BCI) provides a new communication channel between human brain and computer. 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 with employ both independent component analysis (ICA) and oriented principal component analysis (OPCA) for artifact-robust feature extraction.

1. 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[1]. 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 [2]. In this paper pay our attention to an electroencephalogram (EEG)-based BCI system, thus, EEG pattern analysis is critical.

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 [3]. ICA finds a nonorthogonal linear transform with basis coefficients being statistically independent.

On the other hand, PCA is a well-known classical method for dimensionality reduction. In the task of EEG pattern recognition, principal component features were shown to useful [4]. 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 [5]. 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.

2. OPCA

OPCA is an extension of the conventional PCA. In the presence of undesirable subspaces (e.g. 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 . In fact OPCA finds a direction which maximize the generalized Rayleigh quotient for the matrix pencil (R_x, R_v) where R_x is the covariance matrix of the signal and 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

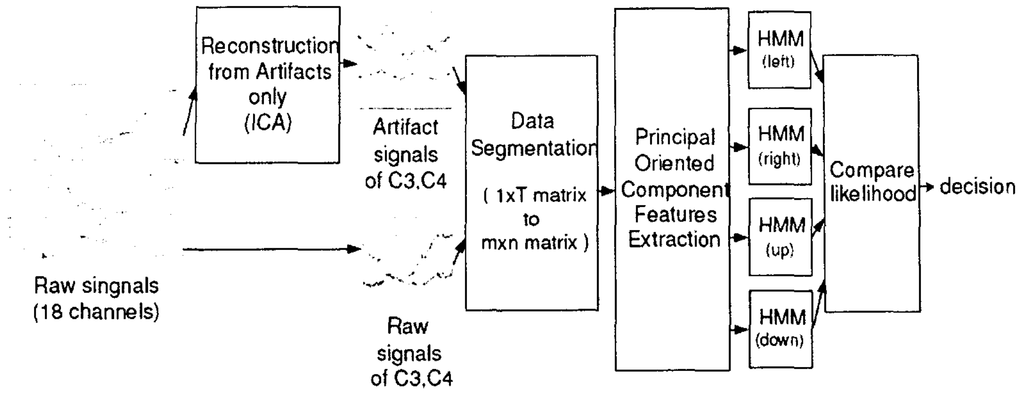

Figure 1. A schematic diagram for our proposed method

vectors x and v:

$$J_{OPCA}(w)=\frac{E\{w^T x\}^2}{E\{w^T v\}^2}=\frac{w^T R_x w}{w^T R_v w} \qquad (1)$$

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 (R_x, R_v). Note that R_v is assumed to be positive definite. The direction w is steered by the distribution of v, in contrast to PCA. When the random vector v has isotropic distribution, OPCA becomes the ordinary PCA.

3. Methods

We consider mainly C3 and C4 channels located in sensorimotor cortex related with (imagery) movements. Figure 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.

4. 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 electro-oculogram (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.

5. Generation of Unwanted Signals by ICA

Given a set of measured EEG data denoted by $X=[x_1, \cdots, x_N]$, ICA finds a linear transformation B such that each column vector of $Y=BX$ consists of statistically independent components. Some components in y_t correspond to artifacts and noise, so their contribution can be eliminated by an inverse mapping B^{-1} with setting the rows in Y corresponding to artifacts to zeros.

In contrast, we keep only artifact components and reconstruct the data by an inverse mapping $V=B^{-1}Y$ with setting the rows in 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 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 [6].

6. Oriented Principal Component Features

We consider the rows in both matrix X and the unwanted signal matrix V. The OPCA considers two correlation matrices, $R_{raw} = X_{raw}X_{raw}^T$ and $R_{noise} = X_{noise}X_{noise}^T$, and solves a generalized eigenvalue problem:

$$R_{raw}W = R_{noise}\Lambda W \tag{2}$$

The row vectors of 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, $W_{C_i,L}, W_{C_i,R}, W_{C_i,U}, W_{C_i,D}$, $i = 3,4$ (L, R, U *and* D correspond to left/right/up/down movement, respectively).

7. Experimental Results

Table 1: 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

Table 2: 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

8. 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.

9. Reference

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