CLASSIFICATION OF SINGLE TRIAL EEG SIGNALS BY A COMBINED PRINCIPAL + INDEPENDENT COMPONENT ANALYSIS AND PROBABILISTIC NEURAL NETWORK APPROACH

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ABSTRACT

In this paper, an attempt is made to classify the EEG signals of letter imagery tasks using a combined independent component analysis and probabilistic neural network. The role of the principal/independent component analysis is to mitigate the effect of EOG artifacts within each single-trial EEG pattern. Experimental results show an overall performance improvement of around 22.2% in terms of the pattern classification accuracy, in comparison with the LPC spectral analysis which is commonly employed in speech recognition tasks.

1. INTRODUCTION

In the last decade, a challenging research direction has come out to explore another communication mode between humans and computers, so called the brain computer interface (BCI), amongst an increasing number of laboratories. The objective of BCI is then to classify the internal states of the human brain measured by means of non-invasive instrumentations such as EEG, MEG, fMRI, or PET devices. This direction is quite significant for the development of new prosthesis devices, which will eventually lead to the benefit of the people with disability. One of the leading groups in BCI, Pfurtsheller, *et. al* [1] or the group by Wolpaw, *et. al* [2], exploits the frequency-domain features such as β or μ rhythms in sensorimotor cortex area for the purpose of, *e.g.*, cursor movement or selection of letters or words on the computer monitor. However, these approach require the subjects to undergo a special training scheme for the stable generation of the two EEG rhythms before its practical use. Other studies focused upon the utility of slow cortical [3] potentials, or P300 potentials [4] in which they claim there is no need for such training but it appears that the approach still is under development for the practical utility.

In this paper, we attempt to enhance the single trial EEG patterns of letter imagery tasks using the components obtained by principal component analysis (PCA) followed by independent component analysis (ICA) for the further reduction of EOG artifacts [5]. We then apply the probabilistic neural network [6] for the pattern classification of the feature vectors obtained by the PCA+ICA data preprocessing with LPC spectral analysis.

2. PATTERN CLASSIFICATION OF EEG SIGNALS

2.1. PCA+ICA for EOG Artifacts Reduction

Let us consider the situation where only N EEG channels out of the N_{max} ($> N$) are available. The task is then to reduce the EOG artifacts (e.g., the myoelectric signals pertaining to eyeball movement) and improve the accuracy of the classification rate, by applying a combined PCA and ICA pre-processing to the N channels. Normally, the standard EEG recording systems have two EOG channels, i.e., HEOG and VEOG (the horizontal and vertical EOG, respectively), which can be exploited to obtain the reference signals for the EOG artifacts reduction.

Let $\boldsymbol{X}$ denote an $(N+2) \times L$ matrix in which the first two rows contain the two EOG signals and rest the N EEG signals (where L denotes the length of a single trial). We assume that each row in $\boldsymbol{X}$ is zero-mean. Then, the covariance matrix of $\boldsymbol{X}$ is calculated as

$$\boldsymbol{V} = \frac{1}{L-1}\boldsymbol{X}\boldsymbol{X}^t. \tag{1}$$

Suppose that the eigenvalue decomposition of the covariance matrix is obtained, i.e.,

$$\boldsymbol{V} = \boldsymbol{U}^T \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_{N+2} \end{pmatrix} \boldsymbol{U} \tag{2}$$

where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_{N+2}$, it is considered that, if we multiply the two EOG channels[1] by a scaling constant K ($>> 1$) before applying the ICA, they will appear on the first two principal components. On the assumption that the first two components correspond to the EOG signals spread over the N EEG channels, we discard the first two principal components, unlike the ordinary utility of PCA in which the components corresponding to the smaller eigenvalues are discarded.

We define a $N \times (N+2)$ matrix $\boldsymbol{P}$ by

$$\boldsymbol{P} = \begin{pmatrix} \frac{1}{\sqrt{\lambda_3}} & & \\ & \ddots & \\ & & \frac{1}{\sqrt{\lambda_{N+2}}} \end{pmatrix} \tilde{\boldsymbol{U}} \tag{3}$$

where $\tilde{\boldsymbol{U}}$ denotes the $N \times (N+2)$ matrix which consists of the last N rows of $\boldsymbol{U}$. Then, the EEG signals after the reduction of the EOG artifacts are obtained by projecting the raw data $\boldsymbol{X}$ onto the last N principal components,

$$\tilde{\boldsymbol{X}} = \boldsymbol{P}\boldsymbol{X}. \tag{4}$$

Next, the EEG data $\tilde{\boldsymbol{X}}$ is uncorrelated, that is,

$$\frac{1}{L-1}\tilde{\boldsymbol{X}}\tilde{\boldsymbol{X}}^T = I, \tag{5}$$

[1] Here, we assume that the amount of EEG components contaminated in the two EOG reference channels is negligible.

which is moderately but not sufficiently separated. We then expect that the classification accuracy will be further improved by separating the uncorrelated components to independent ones before the post-processing (i.e., the stages for LPC and PNN described next) and thus apply ICA to the obtained EEG data $\tilde{X}$. In this paper, we simply use the natural gradient algorithm [7]:

$$\begin{aligned} \boldsymbol{W}(k+1) &= \boldsymbol{W}(k) + \Delta\boldsymbol{W}(k), && (6) \\ \Delta\boldsymbol{W}(k) &= \eta(k)(\boldsymbol{I} - \varphi(\mathbf{y}(k))\mathbf{y}^T(k))\boldsymbol{W}(k), && (7) \end{aligned}$$

where $\eta(k)$ is a learning constant, the activation function is a hyperbolic tangent function, i.e., $\varphi(\boldsymbol{y}) = \tanh(\boldsymbol{y})$, and

$$\mathbf{y}(k) = \boldsymbol{W}(k)\boldsymbol{x}(k) \tag{8}$$

where $\boldsymbol{x}(k)$ denotes the k-th column of $\tilde{\boldsymbol{X}}$. Using the separating matrix $\boldsymbol{W}$, the pre-processed signals are finally given as

$$\boldsymbol{Y} = \boldsymbol{W}\tilde{\boldsymbol{X}} = \boldsymbol{W}\boldsymbol{P}\boldsymbol{X}. \tag{9}$$

2.2. LPC Spectral Analysis

In [8], it is reported that multivariate autoregressive (AR) parameters are effective to represent the features of the EEG patterns for mental imagery tasks. In this paper, rather than the direct exploitation of AR parameters, we use the LPC spectral analysis [9] with a sliding window for the feature extraction, which is well-known technique for speech applications. This strategy is based upon the analytical fact that the AR parameters vary dramatically even between the respective EEG patterns of the same imagery task and thus the direct use of the AR coefficients is considered not suitable for our imagery tasks. This situation is similar to the case of the speech recognition tasks where the speech signals are highly non-stationary.

2.3. The Probabilistic Neural Network

The PNN [6] is a family of radial basis function neural networks (RBF-NNs) [10] and can be seen as the reformulation of kernel discriminant analysis [11] in the artificial neural network context. Recently, the utility of PNN/ generalised regression neural networks

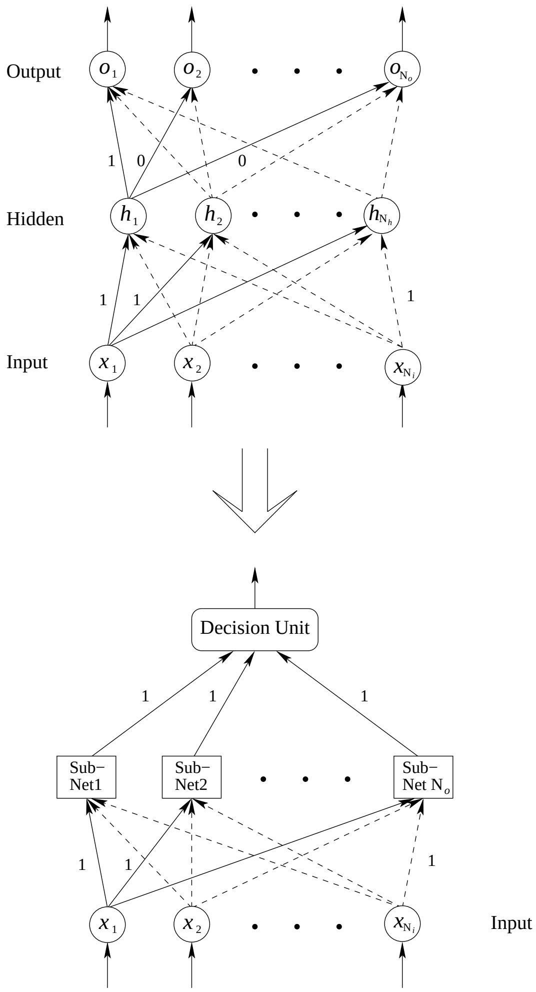

Fig. 1. Illustration of the topological equivalence between a conventional PNN (upper) and that realised modular form (lower).

(GRNNs) has been increased especially in pattern classification, due to its straightforward, quick, and flexible configuration (i.e., network growing/shrinking) property (e.g., see [12]) and robustness, in comparison with e.g., the commonly used multilayered perceptron neural networks [10] trained by a backpropagation type algorithm [13]. Moreover, in [14] it is reported that a PNN even exhibits a capability in accommodating new classes.

In Fig. 1, each input neuron x_i ($i = 1, 2, \cdots, N_i$) corresponds to the element in the input vector $\boldsymbol{x} = [x_1, x_2, \cdots, x_{N_i}]^T$, h_j ($j = 1, 2, \cdots, N_h$) is the j-th RBF (note that N_h is variable), $\|\cdots\|_2^2$ denotes the squared L_2 norm, and the output neuron o_k ($k = 1, 2, \cdots, N_o$) is given as

$$o_k = \frac{1}{\delta} \sum_{j=1}^{N_h} w_{j,k} h_j, \qquad (10)$$

where $\delta = \sum_{k=1}^{N_o} \sum_{j=1}^{N_h} w_{j,k} h_j$, $\boldsymbol{w}_j = [w_{j,1}, w_{j,2}, ..., w_{j,N_o}]^T$, and

$$h_j = exp(-\frac{\|\boldsymbol{x} - \boldsymbol{y}_j\|_2^2}{\sigma_j^2}), \qquad (11)$$

where $\boldsymbol{y}_j$ is called the centroid vector, σ_j is the radius, and $\boldsymbol{w}_j$ denotes the weight vector between the j-th RBF and the output neurons. As in the upper part in Fig. 1, the structure of a PNN is similar to the well-known multilayered perceptron neural network (MLP-NN) except that RBFs are used in the hidden layer and linear functions in the output layer. In Fig. 1, when the target vector $\boldsymbol{t}(\boldsymbol{x})$ corresponding to the input pattern vector $\boldsymbol{x}$ is given as

$$\boldsymbol{t}(\boldsymbol{x}) = (\delta_1, \delta_2, ..., \delta_{N_o}),$$
$$\delta_j = \begin{cases} 1 & \text{if } \boldsymbol{x} \text{ belongs to the class} \\ & \text{corresponding to } o_k \\ 0 & \text{otherwise} \end{cases} \qquad (12)$$

which assigns the weight vector between the j-th RBF and the output neurons, i.e., $\boldsymbol{w}_j = \boldsymbol{t}(\boldsymbol{x})$, the entire network eventually becomes topologically equivalent to the one with a decision unit (followed by the 'winner-takes-all' strategy) and N_o number of sub-nets as in the lower part of the figure [12]. Then, each SubNet i represents the pattern space of Class i spanned by the RBFs. In summary, the network configuration by means of a PNN is simply done as follows:

Network Growing: Set $\boldsymbol{y}_j = \boldsymbol{x}$ and fix σ_j, then add the term $w_{jk}h_j$ in (10). The target vector $\boldsymbol{t}(\boldsymbol{x})$ is used as a class 'label' indicating the subnetwork number to which the RBF belongs.

Network Shrinking: Delete the term, $w_{jk}h_j$, from (10).

As in the above, it is considered that, in hardware implementation, the network growing (learning) can be straightforwardly performed. It is well-known that the generalisation performance of RBF-NN families such as PNNs is robust, while conventional neural networks such as multilayered perceptron neural networks (MLP-NNs) with the backpropagation algorithm [13] require iterative and (quite often) long training whenever the network configuration is changed and is subject to remaining at local minima [10].

3. EXPERIMENT

In the experiment, four (two female/male) external subjects participated to perform the mental imagery tasks and three out of four recorded data sets were found to be usable for the classification tasks. The EEG data were recorded in a dark and both acoustically and electronically shielded room using NEUROSCAN ESI-64 channel system with STIM software package. In the shielding room, each subject sat on a specially designed seat and faced to the display screen at a distance of 280(cm).

3.1. Experimental Design

The objective of the EEG experiment is to classify the two internal brain states between auditory and visual stimulus driven imagery tasks. The experiment thus involved two sessions; one for auditory and the other for visual stimulus driven imagery tasks. In each session, the subjects were asked to start performing the mental imagery of Japanese letter /a/, without any specific control on the imagery (namely, the modality-independent imagery), immediately after the presentation of auditory/visual stimulus. For the auditory stimulus, the vowel /a/ uttered by a native female speaker was presented. In contrast, a letter image of /a/ (in Japanese hiragana character) was displayed in the middle of the screen for the visual stimulus. The subjects were instructed to press the tap button of the response pad once, right after performing each mental imagery task. The trial (i.e., the stimulus presentation followed by the imagery task) was repeated for 45(40) times for one session. Each session then lasted about 5 minutes with a short interval, which was considered to be a reasonable period of time for the subjects to maintain their concentration on performing the imagery tasks without feeling an excessive amount of stress.

3.2. Data Analysis

The raw EEG patterns of the six(five[2]) [8] + two-channel EOG positions, i.e., C3, C4, O1, O2, P3, P4, HEOG, and VEOG, were firstly preprocessed by the PCA+ICA. These eight electrode positions correspond to those of the international standard 10-20 system, which moderately covers from the parietal to occipital area of brain. To better reduce the amount of the EOG components, both the amplitudes of HEOG and VEOG were arbitrarily scaled up to 100 times larger than the original. By applying this setup, it was observed that the EOG artifacts appeared in the top two channels after the PCA and ICA were satisfactorily removed from the six positions.

The PNN classifier was then constructed (trained) using the feature vector which consists of the normalised LPC spectra of the six-channel PCA+ICA preprocessed signals obtained from the first 30(25) trials, (i.e., in the experiments, each feature vector was simply allocated to an RBF in the network) and the remaining 15 patterns were used for testing. The order of the AR model was empirically determined to 10, whereas the number of the analysis frames for LPC was set to 16.

For comparison, another PCA classifier and the testing data set were prepared, with directly applying the conventional LPC spectral analysis to the raw EEG signals obtained from the six(five[2]) positions C3, C4, O1, O2, P3, and P4 [8].

Figs. 2 and 3 respectively show an example of the results obtained by PCA and those of PCA followed by ICA. As shown in Fig. 2, it was confirmed that the EOG activity appeared in the top two PCA components, PCA1 and PCA2, for most of the trials, whilst those are still remaining in other components, i.e., PCA3, PCA4, and PCA6. However, other unseen components in the raw data are emerged in other PCA components, e.g., PCA4 and PCA5. In contrast, in Fig. 3, it can be seen that the separation of the components is slightly improved. This separation is particularly eminent for ICA1 and ICA2. In summary, we confirmed that the amount of the EOG artifacts can be effectively reduced by the hybrid scheme of PCA and ICA.

[2] For some data, only five out of the six electrode positions were available, due to the bad contact between the scalp and electrodes which resulted in high impedance channels.

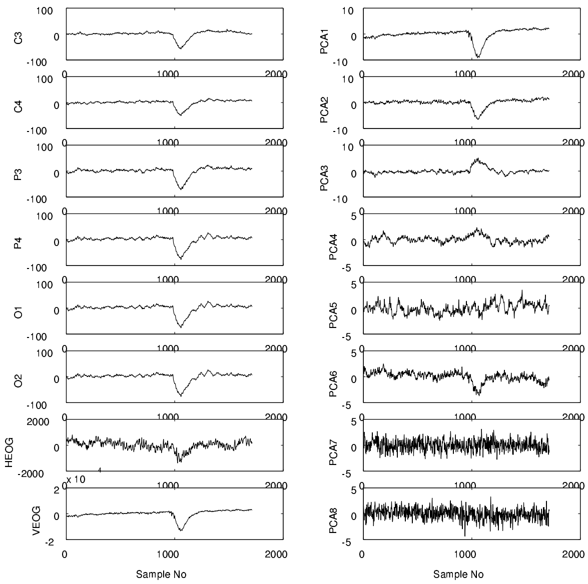

Fig. 2. Data Analysis by PCA.

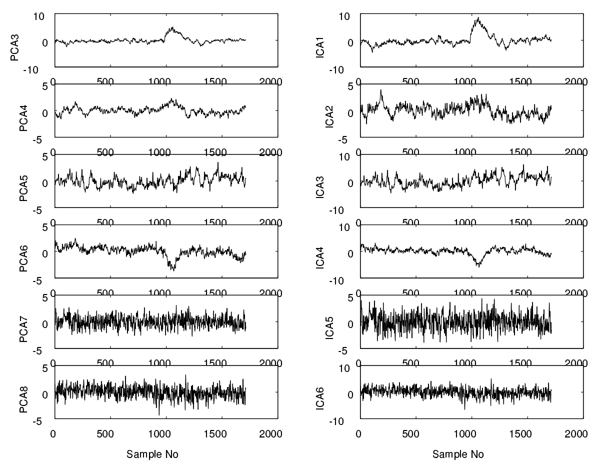

Fig. 3. Data Analysis by PCA followed by ICA.

3.3. Classification Results

Table 1 summarises the classification results of the above two methods; one for directly applying the LPC spectral analysis and the other for the analysis after the EOG artifacts reduction. As shown, the performance improvement of around $17 - 30\%$ in terms of classification rate was obtained for all the cases.

	Classification performance	
	without EOG reduction	with EOG reduction by PCA+ICA
Subject 1	56.7%	76.7%
Subject 2	60.0%	76.7%
Subject 3	50.0%	80.0%
Average	55.6%	77.8%

Table 1. Comparison of the classification performance.

	Sample No					
	Imagery with auditory stimulus			Imagery with visual stimulus		
	Avg.	Min.	Max.	Avg.	Min.	Max.
Subject 1	241	150	458	744	578	1081
Subject 2	1869	1267	2316	2096	1575	2563
Subject 3	593	264	1019	5732	901	14787

Table 2. Comparison of the analysis window lengths between the subjects.

3.4. Discussion

In the experimental design, we did not control the duration for imagery tasks, and thus the sample number of trials (i.e., the analysis window length; the window length was varied according to both the timing of the subject's button pressing, which gave the end point of the window, and the starting point, which, for the auditory stimulus, is right after the presentation was finished, and in contrast, for the visual stimulus, was identical to the stimulus presentation.) differs from each other. Then, one of the concerns may be that the classification tasks were carried out by not the difference in the EEG components but merely the analysis window length. However, from the comparison of Table 1 with Table 2, it is justified that the classification rate is independent from this factor.

4. CONCLUSION

In this paper, pattern classification of single-trial EEG signals obtained for mental imagery tasks has been performed. Although it has been observed the consistent performance improvement using the PCA+ICA approach, compared to the conventional LPC spectral analysis, for the three out of four data, the classification results obtained in this work are considered to be preliminary and a number of issues are still remained to be open. For instance, we still are not convinced if the classification results were really obtained from the consequence of distinguishing the mental imagery tasks. We thus need a thorough neurophysiological/ cognitive-scientific investigation of the results so obtained as well as the data analysis, which is beyond the scope of this paper, and, as the first step, plan to continue the EEG experiments in a similar manner to that presented in this paper, but with a more elaborate design by giving constraints to the subjects, e.g., specific imagery tasks depending upon the stimuli given or introducing fixed duration of time for imagery tasks. In parallel to this, future work also includes the extension to biofeedback-type mental imagery tasks by exploiting the quick and flexibly reconfiguration property of the PNN classifiers.

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