35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Automatic Design for Independent Component Analysis based Brain-computer Interfacing

Chun-Hsiang Chuang, *Member, IEEE*, Yuan-Pin Lin, *Member, IEEE*, Li-Wei Ko, *Member, IEEE*, Tzyy-Ping Jung, *Senior Member, IEEE*, and Chin-Teng Lin, *Fellow, IEEE*

Abstract—**This study proposes a new framework, independent component ensemble, to leverage the acquired knowledge into a truly automatic and on-line EEG-based brain-computer interfacing (BCI). The envisioned design includes: (1) independent source recover using independent component analysis (ICA) (2) automatic selection of the independent components of interest (ICi) associated with human behaviors; (3) multiple classifiers with a parallel constructing and processing structure; and (4) a simple fusion scheme to combine the decisions from multiple classifiers. Its implications in BCI are demonstrated through a sample application: cognitive-state monitoring of participants performing a realistic sustained-attention driving task. Empirical results showed the proposed ensemble design could provide an improvement of 7%~15% in overall accuracy for the classification of the arousal state and the driving performance. In summary, constructing ICi-ensemble classifiers and combining their outputs demonstrates a practical option for ICA-based BCIs to reduce the risk of not obtaining any desired independent source or selecting an inadequate component. Most importantly, the ensemble design for integrating information across multiple brain areas creates potentials for developing more complicated BCIs for real world applications.**

I. Introduction

Over the last few decades, electroencephalography (EEG), the electric current produced by the activity of the brain, has been proven to be a robust physiological indicator used to characterize human behaviors. Several EEG-based brain-computer interfaces (BCI) have been proposed and developed for real-life applications such as fatigue monitoring, alertness evaluation, or accident prevention [1, 2]. However, suboptimal performances resulting from a poor signal-to-noise ratio (SNR) of measured EEG signals in real operational environments still hindered the transition of laboratory-oriented neuroscience research to practical BCI devices.

Recently, independent component analysis (ICA) [3] has been widely adopted to deal with the pervasive EEG contaminations arising from eye blinks, eye movements, muscle activities, and so on. ICA decomposes multichannel EEG signals into spatially fixed and maximally temporally independent component (IC) processes. Applying machine-learning techniques to assess the brain dynamics of different ICs had been shown to effectively enhance the system performance [4, 5]. However, how to automatically select informative IC(s) is an important issue for the practical applications in the real environment. Most existing ICA-based models use a predefined independent component of interest (ICi). In human performance studies, poor task performance might be caused by failure to functionally engage multiple brain processes. Hence, combining related brain processes to characterize complex human behaviors intuitively appears to be more reasonable than using only one or few specific processes. Further, ICA, applied to multi-channel EEG, produces unordered ICs. Although component scalp maps [6] help in recognizing the types of sources, selecting task-related ICi or discarding artifactual ICs often still requires manual intervention of an expert or experts. More importantly, ICs obtained from different subjects might vary widely, i.e., some ICs might be present in recordings from one subject but not from another. Most ICA-based BCI systems, particular systems using one or two specific ICi, would fail if none of the IC matches the target ICi. Under these circumstances, using an ensemble of ICs strategy selected by an automatic scheme to build an ICA-based BCI system is practically feasible.

II. Independent Component Ensemble

A. System Diagram

Following the design guideline of a classifier ensemble or multiple classifier system [7], this study proposed an independent component ensemble system using multiple ICi (as shown in Figure 1) to build a brain-computer interface, aiming to overcome the above-mentioned problems. First, the templates of spatial maps [6] of the ICi were generated from our previous driving studies [4], in which the selected ICi was predefined based on the prior knowledge in EEG correlates of driving performance. Then, an automatic selection scheme searched target ICi from all ICs separated by ICA based on a simple similarity measurement. Second, fast Fourier transform (FFT) and feature extraction were used

This work was supported in part by the UST-UCSD International Center of Excellence in Advanced Bio-engineering sponsored by the Taiwan National Science Council I-RiCE Program under Grant Number: NSC-101-2911-I-009-101, in part by the Aiming for the Top University Plan of National Chiao Tung University, the Ministry of Education, Taiwan, under Contract 101W963, and in part by the National Science Council, Taiwan, under Contract 100-2628-E-009-027-MY3. Research was also sponsored in part by the Army Research Laboratory and was accomplished under Cooperative Agreement Number W911NF-10-2-0022.

C.-H. Chuang and C.-T. Lin are with the Institute of Electrical Control Engineering and the Brain Research Center, National Chiao Tung University, Taiwan. (e-mail: cch.chuang@gmail.com; ctlin@mail.nctu.edu.tw).

L.-W. Ko is with the Department of Biological Science and Technology and the Brain Research Center, National Chiao Tung University, Taiwan (e-mail: lwko@mail.nctu.edu.tw).

T.-P. Jung is with the Swartz Center for Computational Neuroscience and Center for Advanced Neurological Engineering, University of California, San Diego, USA (e-mail: jung@sccn.ucsd.edu).

978-1-4577-0216-7/13/$26.00 ©2013 IEEE

to obtain spectral changes most characterizing brain dynamics. Third, a machine-learning classifier was built for each ICi to construct a classifier ensemble. The training procedure could be done in parallel to dismiss doubts about computation time. Finally, a decision-fusion method integrated outputs of all classifiers to make a final classification. The following sections describe the details of each EEG signal-processing step.

B. Automatic ICi Selection

Assume that the time courses of n-channel EEG signals (X) receive an unknown linear combination of n-IC (Y). This mixing model is written as:

$$\mathrm{X} = \Lambda \times \mathrm{Y}, \tag{1}$$

where Λ denotes a mixing matrix. In other words, each IC contributes to the scalp EEG sensors through a spatial filter, i.e., the column of Λ. By implementing ICA, an unmixing matrix (the inverse of the mixing matrix) can be obtained such that the underlying processes are statistically independent.

Moreover, each spatial filter representing the projection strengths from a source to all EEG sensors could be rendered as a 2D scalp topography for source identification [6]. Technically, each map shown in Fig. 2 is the average ICA weights from the result of different subjects participating in our previous works [4]. Our previous study [8] has shown that the brain activations near or within the frontal, central, motor, parietal, and occipital regions were highly related to the changes in driving performance. Therefore, the scalp topographies of these five component maps were used as the spatial templates of ICi, $\hat{\Lambda} = \{\hat{\Lambda}_1, \hat{\Lambda}_2, \ldots, \hat{\Lambda}_5\}$ for automatic ICi selection. All the columns of Λ obtained by ICA were correlated with each template using Pearson's correlation coefficient. If the correlation exceeds a pre-set value (e.g. 0.8), the corresponding ICi was selected for further processing. Note that it is necessary to take the absolute value of the correlation coefficient so as to select the ICi potentially having a reverse polarity. Additionally, both arrays were scaled in the range of $[-1, 1]$ before estimating the correlation coefficient.

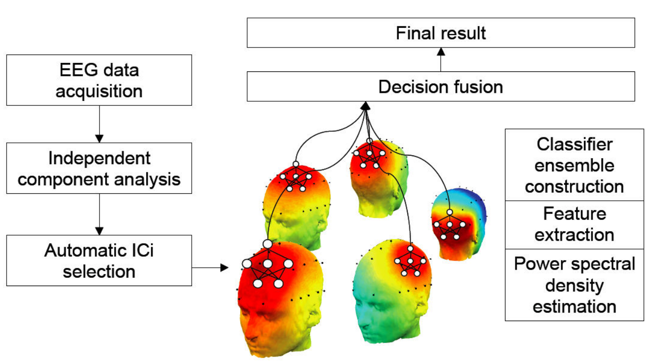

Figure 1. Schematic diagram of the component ensemble classifications.

C. Power Spectral Density Estimation

To simultaneously characterize a short-term and a long-term change in brain activities, we performed a 256-point FFT (sub-window: 128-point; zero-padding; 256-point) for both 1-s and 90-s epochs of ICi signals. The dimensions for resultant power spectral densities, $\mathrm{V}_{1\text{-s}}$ and $\mathrm{V}_{90\text{-s}}$, consisted of 30 frequency bins from 0.98 to 30.3 Hz with a frequency resolution near 1 Hz. For the spectral representation of the *i*th-ICi, two spectral arrays were averaged:

$$\overline{\mathrm{V}}_i = \frac{\mathrm{V}_{1\text{-s}} + \mathrm{V}_{90\text{-s}}}{2}, \tag{2}$$

where $\overline{\mathrm{V}}_i \in \mathrm{R}^p$ and $p = 30$ in this study.

D. Feature Extraction

The proposed ensemble allows the classifiers to learn diverse spectral information from different ICi. To improve the efficiency of the ensemble classification, a dimension-reduction procedure was used to build the classifiers. The feature extraction extracted informative features from the original space R^p into a reduced space R^q, where $q \leq p$. Given a transformation matrix for each ICi, the feature extraction performed a linear mapping such that the transformed data preserved the relevant information. Criteria for assessing the transformation matrix in terms of the optimal features could be accomplished using several approaches and measurements such as a heuristic search, a statistical variability of data, or a class separability. This study applied several well-known algorithms, including sequential forward selection (SFS), principal component analysis (PCA), linear discriminate analysis (LDA) [9], and nonparametric weighting feature extraction (NWFE) [10] for the comparison of classification performances.

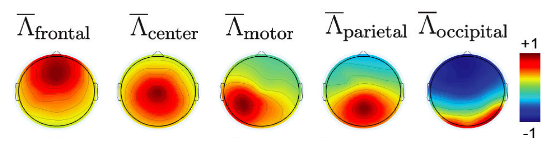

Figure 2. Weighting patterns of templates of ICi

E. Classification Ensemble and Decision Fusion

The dimension-reduced data W_i and the corresponding class-label $\mathrm{Y} = \{1, 2, \ldots, L\}$ (L is the number of classes) were then used to train the parameters of the classifier. Note that the ensemble size *d*, i.e., the number of the classifiers, is equal to the number of ICs whose scalp maps match the spatial templates of ICi. The value of *d* thus varies from subject to subject. In the fusion system, a simple majority vote scheme integrated all the outputs of classifiers to make a final decision. The operation of the majority voting can be derived by:

$$\operatorname*{argmax}_{\ell \in \{1,2,\ldots,L\}} card(i \mid o_i = \ell, i = 1, 2, \ldots, d), \tag{3}$$

where $card(.)$ denotes the cardinality of the set.

III. System Validation

A. Virtual-reality based Driving Simulator and Experimental Paradigm

A virtual-reality based high-fidelity driving environment [4] was constructed to study the neurophysiological activity in response to complex driving behaviors. Seven personal computers projected a synchronized animation of a four-lane highway scenario onto fully immersive 360-degree walls through seven projectors at different viewing angles. The refresh rate of the highway scene was set properly to emulate a car cruising at a fixed speed of 100 km/hr. At the center of the driving simulator, a real car was mounted on a six-degree-of-freedom motion platform that simulated the movements of real driving. The event-related land-departure paradigm [11] was implemented in the driving simulator. This paradigm mimics a non-ideal road surface that makes the car randomly drift away from the cruising lane. The participant was instructed to steer the car back to the center of the original lane as soon as possible when facing each random car perturbation.

B. EEG Data Acquisition and Class Assignment

Ten volunteer subjects with normal or corrected to normal vision participated in the driving experiments. For EEG data acquisition, a Scan NuAmps Express system (Compumedics USA Inc., Charlotte, NC) recorded 30-channel EEG signals with a 16-bit quantization level at a sampling rate of 500 Hz by Ag/AgCl electrodes. The impedance of all of the electrodes was maintained below 5 kΩ during the experiment. To reduce the data size and remove noise, the data were down-sampled to 250 Hz and filtered with a band-pass FIR filter (1~50 Hz) before further analysis.

According to the observed reaction time (RT) in response to the lane-departure event and the average of RTs ($\overline{\mathrm{RT}}$) observed in a 90-s window, each trial was labeled by quantifying the driving performance (i.e., high: $\mathrm{RT} \leq 0.7\mathrm{s}$ and low: $\mathrm{RT} \geq 2.1\mathrm{s}$) and putative cognitive states (i.e., alert: $\overline{\mathrm{RT}} \leq 0.7\mathrm{s}$ and drowsy: $\overline{\mathrm{RT}} \geq 2.1\mathrm{s}$). Hence, there were four classes of EEG trials: “alert state with high performance”, “drowsy state with low performance”, “alert state with low performance”, and “drowsy state with high performance”.

C. Classification Validation

The signal processing of this study, including band-pass filtering and ICA, uses EEGLAB ToolBox [6]. To reduce the computational time, only the features that guaranteed the optimal subset in SFS or the eigenvectors with the largest eigenvalues in PCA, LDA, and NWFE were used for classification, i.e., $p = 1$. The LIBSVM [12] was used to construct the classifiers for SVM (with radial basis function). To obtain reliable accuracy, a leave-one-subject-out cross-validation process, which used the samples from a single subject as the validation data and the samples from the remaining subjects as the training data, was repeated for ten subjects. All the parameters of the feature extractions and the classifiers were calculated from the training data and applied to the testing data. Training and testing data were totally disjoint. In the final voting step, the decision-making process would randomly choose one of the classes to break a tie vote if no class had majority votes.

A similar concept of the ensemble system could also be applied to the EEG channels of interest. If none of the IC matches any of the templates of ICi, we could easily change the BCI system from the ICA-based ensemble to an electrode-based ensemble. This study would provide the result of the ensemble system using channel-domain signals as the benchmark to test the effectiveness of the proposed ICi ensemble approach. We used signals from Fz, Cz, T7, Pz, and Oz channels in this drowsiness-detection application.

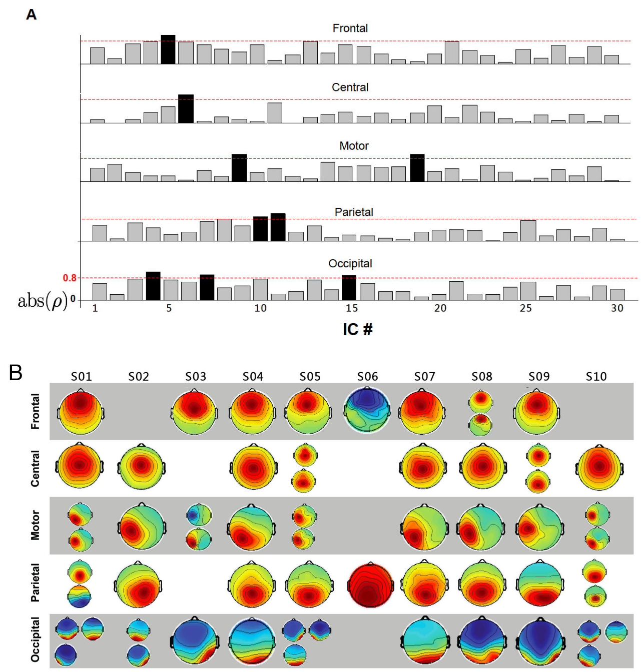

Figure 3. Results of the ICi seleciton for (A) subject01 and (B) ten subjects. The dark bars indicate the scalp maps of the IC had a high similarity with the templates. The red dash line is the threshold for the correlation coefficient of 0.8.

IV. Results and Discussions

A. Adaptive Ensemble Size

Figure 3A shows the results of a similarity test of the ICi selection for a sample subject (subject01). In this study, if the correlation coefficients between spatial templates (Fig. 2) and ICA-extracted components (upper panel in Fig. 3A) are over 0.8, the corresponding temporal IC activation was selected as ICi. Figure 3B shows the results of the ICi selection across ten subjects. The averages of the absolute values of the correlation coefficients between selected maps and predefined templates were 0.978, 0.957, 0.925, 0.943, and 0.853 for the frontal, central, motor, parietal, and occipital components, respectively. As expected, different subjects had different numbers of ICi. The individual variability in the ICi selection led the resultant BCI to be a subject-dependent system. The ensemble sizes for s01 to s10 were 9, 5, 4, 5, 9, 2, 5, 6, 6, and 8, respectively.

TABLE I. THE AVERAGED CLASSIFICATION ACCURACY OF THE ENSEMBLE SYSTEM USING CHANNEL-DOMAIN SIGNALS.

Feature extraction	Classifier	Channel					Ensemble
		Fz	Cz	T7	Pz	Oz	
SFS	**SVM**	63.0±3.8	65.2±2.3	55.6±9.3	73.3±4.8	72.0±6.9	77.3±3.4*
PCA		66.1±5.0	59.9±4.6	53.7±6.9	65.3±7.7	60.7±5.4	67.1±4.0
LDA		64.9±5.6	69.9±6.2	57.7±10.7	64.9±6.5	59.9±4.0	71.0±5.1
NWFE		73.2±4.2	74.9±4.9	59.2±7.2	75.3±4.2	72.8±5.8	**79.8±3.5***

Each cell represents the classification accuracy ± standard deviation (in %). The asterisk denotes a significant difference in the mean value between the classification accuracy of using one channel (with the highest accuracy) and the proposed ensemble, where *: p-value<0.01.

TABLE II. THE AVERAGED CLASSIFICATION ACCURACY OF THE PROPOSED ENSEMBLE USING INDEPENDENT COMPONENTS.

Feature extraction	Classifier	ICi					Ensemble
		Frontal	Central	Motor	Parietal	Occipital	
SFS	**SVM**	78.1±6.9	72.6±9.2	75.6±8.4	84.1±8.0	77.2±7.7	88.1±1.5*
PCA		67.9±7.3	62.9±4.6	54.1±4.5	69.2±4.7	64.9±8.4	75.9±2.9
LDA		64.7±3.9	69.9±5.6	65.7±5.3	68.2±5.6	65.7±2.9	79.7±1.4*
NWFE		79.5±3.7	80.0±2.2	80.9±4.0	84.3±2.4	82.8±2.8	**91.6±1.1***

Each cell represents the classification accuracy ± standard deviation (in %). The asterisk denotes a significant difference in the mean value between the classification accuracy of using one ICi (with the highest accuracy) and the proposed ensemble, where *: p-value<0.01.

B. *Classification Accuracy*

Table I shows the summary of classification accuracy (the average and the standard deviation of the accuracy) using scalp-recorded EEG signals. The last column in Table I lists the classification results obtained by the ensemble classification. An asterisk is placed next to the number that reaches a statistically significant improvement compared to the highest accuracy of the SVM using one channel signal. The ensemble approach significantly improve the classification accuracy from 60~75% to 79.8%. Table II compares the classification results between all feature extraction methods with a SVM classifier by using ICi signals. Compared to the ensemble system using original signals without ICA, the proposed ensemble system successively improved the classification accuracy and reduced the standard deviation in most of the cases. For example, using NWFE with SVM, the accuracy increased from 79.5% (frontal), 80.0% (central), 80.9% (motor), 84.3% (parietal), and 82.8% (occipital) to 91.6% (ensemble); moreover, the standard deviation decreased from 2.2%~4.0% to 1.1%. These results proved that the proposed ensemble approach could obtain a better classification, rather than being at risk of taking a suboptimal solution based on pre-defined component(s).

V. CONCLUSIONS

This study proposed an independent component ensemble to integrate information from multiple brain regions and overcome the subject variability in resultant independent components. By combining ICA, automatic ICi selection, feature extraction, classifier determination, and a decision-fusion method, a truly automatic, on-line BCI system can be effectively constructed for real-life applications.

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