AsEmo: Automatic Approach for EEG-Based Multiple Emotional State Identification

Sun-Hee Kim, Hyung-Jeong Yang, Ngoc Anh Thi Nguyen, and Seong-Whan Lee, *Fellow, IEEE*

***Abstract*—An electroencephalogram (EEG) is the most extensively used physiological signal in emotion recognition using biometric data. However, these EEG data are difficult to analyze, because of their anomalous characteristic where statistical elements vary according to time as well as spatial–temporal correlations. Therefore, new methods that can clearly distinguish emotional states in EEG data are required. In this paper, we propose a new emotion recognition method, named *AsEmo*. The proposed method extracts effective features boosting classification performance on various emotional states from multi-class EEG data. *AsEmo* Automatically determines the number of spatial filters needed to extract significant features using the explained variance ratio (EVR) and employs a *S*ubject-independent method for real-time processing of *Emo*tion EEG data. The advantages of this method are as follows: (a) it automatically determines the spatial filter coefficients distinguishing emotional states and extracts the best features; (b) it is very robust for real-time analysis of new data using a subject-independent technique that considers subject sets, and not a specific subject; (c) it can be easily applied to both binary-class and multi-class data. Experimental results on real-world EEG emotion recognition tasks demonstrate that *AsEmo* outperforms other state-of-the-art methods with a 2–8% improvement in terms of classification accuracy.**

***Index Terms*—Electroencephalogram, emotion recognition, explained variance ratio, feature extraction, multi-class common spatial pattern, subject-independent.**

I. Introduction

EMOTION recognition is a technique in which human emotion is read using voice, facial expressions, and physiological signals. Emotion recognition technologies are employed in various fields, such as entertainment, healthcare, market research, on-line education, automobile industry, and robotics. However, it is still difficult to analyze an exact emotion by the differences in the variables, such as facial expression, voice tone, pitch, volume, and speed. In addition, the intensity of a feeling and the expressed emotion differ between individuals. In recent years, signicant studies have been conducted to understand human emotional states by analyzing physiological signals including blood pressure, heart rate, and even organ movement. Specifically, EEG data, which are generated by the central nervous system (CNS), are generally used in emotion recognition research [1].

An EEG is the electrical flow that is generated when a signal is transferred between the cranial nerves in the nervous system. These signals differ based on the state of the body and mind, and are important indicators for measuring the state of brain activity. In the fields of medicine and psychology, EEGs have been employed in quantitative research by signal processing technology for diagnosing and predicting brain diseases, such as epilepsy or Parkinson's disease [2], [3]. Another use of EEGs is to study cerebral nervous and degenerative brain diseases that exhibit dyskinesia (such as cerebral apoplexy, progressive bulbar palsy, and spinal muscular atrophy), for measuring concentration, for diagnosing depression, BCI for the spelling systems, and in rehabilitation robots [4]–[7]. Furthermore, various EEG-based emotional state recognition studies have been continually investigated because of its reliable evaluation compared with those of other physiological signals, particularly following the discovery of an area in the brain that can control emotions [8], [9].

The emotion recognition technique using EEGs is primarily divided into pre-processing, feature extraction, and classification processes. In particular, feature extraction is a process that accentuates the features of the EEG data for facilitating classification. This step extracts important features that can identify emotional states. In the field of emotion recognition, the most frequently used feature extraction methods are the short-time Fourier transform (STFT) [10] or discrete Fourier transform (DFT) [11] based on the Fourier transform, power spectral density (PSD) [12],

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wavelet transform (WT) [13], entropy (such as approximate entropy (AE), differential entropy (DE), sample entropy (SE), and wavelet entropy (WE) [14]), higher order crossings (HOCs) [15] and common spatial patterns (CSP) [16]. However, these methods are usually applicable to single-channels and mostly focus on the spectral power change in a fixed frequency band. To overcome the above mentioned limitations, alternative feature extractions based on multi-channels have been proposed including multiclass common spatial pattern (MCSP) [17], Hybrid Adaptive Filter-Higher Order Crossing (HAF-HOC) [18], and minimum–Redundancy–Maximum Relevance (mRMR) [19].

In the classication stage, diversity classier techniques that apply to the extracted features such as logistic regression [17], K-nearest neighbor (KNN) [11], support vector machine (SVM) [13], and multi-layer perceptron (MLP) [20] have been used. Those classifiers are mostly trained by the subject-dependent method. However, a subject-dependent method is suitable only for the provided data because it trains the classifier from specific subject data. In other words, this method needs to re-train to process new data for improving the classification performance. In contrast, because a subject-independent method trains the classifier from the subject dataset and not from the data of a specific subject, when new data are entered into the analysis system, it can provide a good classification performance without re-training.

In this paper, we propose the *AsEmo* method to improve the classification accuracy by detecting the features in accordance with the emotional state based on multi-class EEG data. The major contributions of our approach are as follows:

- **Careful feature extraction:** *AsEmo* automatically determines the number of features by applying the explained variance ratio (EVR) to the sum of the covariance matrices of all the classes in the feature extraction process to classify the emotional state.
- **Effectiveness:** Our method performs feature extraction using the training dataset based on a subject-independent method. Therefore, this enables the application of *AsEmo* to real-time data, because the classifier is not required to be trained for new data.
- **Applicability:** It can provide high classification accuracy for binary-class data as well as multi-class data. In addition, it can be used for other real-time data analysis.

The remainder of this paper is organized as follows. Section II discusses the related works on emotion recognition using EEGs. Section III presents our proposed method for extracting features according to emotional states based on real-time analysis. Section IV describes the experimental results, and Section V provides the discussion of this work. Finally, Section VI presents the conclusions drawn from the study.

II. Related Works

Emotion recognition research using EEG signals requires the feature extraction step to clearly identify the emotional states. Alsolamy and Fattouh [12] used PSD to extract various frequency bands as features that could distinguish two emotional states, "happy and unhappy," when listening to Quran music. Yusuf *et al.* [11] recorded EEG signals through 24 channels from subjects that experienced audio-visual stimuli for 5 min, for mental emotion analysis. They used the DFT and PSD methods to extract the features and a K-NN classifier to recognize four classes including happy, sad, scared, and disgusted. However, this method only displays frequency components while analyzing the characteristics of an EEG. Thus, it leads to a drawback in expressing the EEG as a function of time.

To analyze the time domain, Basar *et al.* [16] used the CSP method, which is one of the best performing methods in emotion estimation applications, to analyze the collected EEG signals. Patil *et al.* [15] measured the EEG signal related to both happy and sad emotions using single-channel PowerLab Instrument equipment. They filtered the EEG data using a band pass between 0 and 30 Hz and subsequently extracted the features by applying HOCs to the pre-processed EEG data. The STFT [10] and WT [13] methods could express the interpretation of both the frequency and temporal domains. Jalilifard *et al.* [10] extracted features using an STFT for identifying two emotional states. Mohammadi *et al.* [13] proposed emotion recognition algorithms based on EEGs that could extract features using a temporal window of a WT and classify the emotional states using SVMs and a K-NN classifier. However, although WT decomposes a signal into approximation and detail components, it fails to reflect the relevant information existing locally in the high-frequency components. In addition, the above-mentioned studies have been performed primarily for binary-class emotion recognition.

For multi-class emotion recognition, Wentrup and Buss [17] extracted the features using MCSP based on the joint approximate diagonalization (JAD) that extended the CSP for binary-class data. Petrantonakis and Hadjileontiadis [18] separated the characteristics related to the emotion EEG signals by HAF-HOC, and subsequently the efficient feature vectors were extracted by selecting the optimal intrinsic mode functions (IMFs) by an iterative sifting process. Atkatkin and Campos [19] extracted the statistical features, band power(BP) for different frequencies, Hjorth parameters (HP), and Fractal dimension (FD) from all channels, and the median, standard deviation, and kurtosis coefficient were used as the statistical features. Furthermore, theta (4–8 Hz), low alpha (8–10 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–50 Hz) frequency bands were included as the primary features, and the best features were extracted by applying mRMR. However, those feature extraction methods for the multiclass EEG data provided a low recognition rate or low classication accuracy, and required significant computation time owing to the number of features.

In EEG-based emotion recognition studies, previous classifiers such as logistic regression, K-NN, and SVM were applied for subject-dependent recognition. However, those subject-dependent classification approaches create a challenge for real-time processing because they required significant retraining time if new data was entered into the system [21]. Oh [21] used a subject-independent classifier for distinguishing the implicit intention of the unanalyzed users in the EEG data. Xu and Plataniotis [22] performed leave-one-subject-out cross-validation on the MAHNOB-HCI-Tagging database for emotional state classification. Soleymani *et al.* [23] extracted features using the PSD from EEG data and performed cross-subject emotion recognition. Kortelainen and Seppanen [24] evaluated the cross-subject classification rates of valence and arousal in a 1–32 Hz feature subset. Zheng *et al.* [25] proposed a subject-independent classification for detecting stable neural EEG patterns across subjects and sessions. Similar to this, cross-subject classification-study-based subject-independent is rarely applied as a classification learning method for real-time data analysis. Thus, we apply the subject-independent method performing with adequate accuracy in real-time applications.

III. Proposed Method

A. CSP for Binary Classes

The CSP method is a representative EEG feature extraction method, which is extensively used in motion recognition for brain–computer interfaces (BCIs) [26], [27]. The CSP has been applied to extract emotional features for emotion recognition in numerous previous studies [28]–[30][31]. Furthermore, the extension of CSP and combination CSP with other methods have been recently proposed in the publication of [16], [32], [33]. CSP determine the spatial matrix that maximizes the variance of each class, when the data consist of two classes [16]. Specifically, it simultaneously detects the direction vectors that maximize the data variance of one class and those that minimize the data variance of the other class. Subsequently, these direction vectors adopt the roles of spatial filters, emphasizing the part possessing the greater influential power to distinguish the binary classes [34].

Given an EEG matrix recorded according to the emotional state of a subject, X_i, and the covariance matrix, C_i, where $i \in \{1, 2\}$ and X_i consists of channels (row) and time (column). C_i includes all the trials of X_i and is a square matrix whose dimensions correspond to the number of channels, which indicate the number of electrodes attached to the scalp. Therefore, the CSP methods determines the vector W that can maximize the difference between classes 1 and 2 as follows:

$$W = \arg\max_{W} \left\{ \frac{W^T C_1 W}{W^T C_2 W} \right\}. \tag{1}$$

The optimization problem in Eq. (1) can be solved with a generalized eigenvalue problem as expressed in Eq. (2), where the generalized eigenvector corresponds to the spatial filter.

$$C_1 W = \lambda C_2 W. \tag{2}$$

Initially, the CSP method was designed for extracting features from binary-class data; subsequent research led to this method being extended to feature extraction from multi-class data [17], [35].

B. MCSP for Multi-Classes

Given a multi-class EEG matrix recorded according to the emotional state of a subject, $X_i^k, i \in \{1, \ldots, I\}$, the covariance matrix of each class computes with Eq. (3) using an MCSP.

$$C_i = \sum_{k=1}^{K} (X_i^k - \frac{1}{K} \textstyle\sum_{k=1}^{K} X_i^k)(X_i^k - \frac{1}{K} \sum_{k=1}^{K} X_i^k)^T, \tag{3}$$

where i denotes the class labels of the subject, k represents the number of trials at class label i, and X denotes an EEG data matrix of $n * t$ with n channels and t time points.

The covariance matrix of each trial corresponding to the emotional state class label, i, as obtained from Eq. (3), is normalized, as expressed in Eq. (4). The mixed-covariance matrix, C, is obtained as the sum of the covariance matrices of all the class labels, as expressed in Eq. (5).

$$C_i = \frac{1}{k} \sum_{i=1}^{I} \frac{C_i}{trace(C_i)}. \tag{4}$$

$$C = C_1 + \cdots + C_i. \tag{5}$$

The mixed-covariance matrix, C, can be factored using eigenvalue decomposition as follows:

$$C = U \Lambda U^T, \tag{6}$$

$$W = \Lambda^{-\frac{1}{2}} U^T, \tag{7}$$

where U is an $n * n$ unitary matrix of the eigenvectors and Λ is an $n * n$ diagonal matrix of the eigenvalues. The whitening transformation matrix, W, is calculated using U_0 and Λ, which are obtained using the eigenvalue decomposition of the mixed-covariance matrix, C, as expressed in Eq. (7). W normalizes the value of the transformed data by converting the covariance matrix of the transformed signals into a unit matrix and converting the variance to 1 simultaneously.

To extract the spatial patterns with respect to the emotional state from a dataset composed of multi-classes using the MCSP, we employed the one-versus-the-rest (OVR) method [36]. The OVR method assesses one class as C_1 in the multi classes and the others as class $C_I^{'}$, where $C_I^{'} = C_2 + \cdots + C_i$. The unit matrix is expressed as Eq. (8) when conducting the whitening transformation on the mixed-covariance matrix, C, which is obtained from Eq. (5).

$$WCW^T = WC_1W^T + WC_I^{'}W^T = S_1 + S_{2+\cdots+i} = I, \tag{8}$$

where S is the whitened matrix using the whitening transformation matrix, and S_1 and $S_{2+\cdots+i}$ share common eigenvectors. Specifically, we can arrange the eigenvalue matrix as follows:

$$\Lambda_1 = I - \Lambda_{2+\cdots+i}. \tag{9}$$

Eq. (9) indicates that class 1 and the other classes, $(2 + \cdots + i)$, have an inverse relationship. The eigen-decomposition of the whitened matrix, $(S_1, S_{2+\cdots+i})$, with the common eigenvector, $U^{'}$, can be expressed as Eq. (10).

$$S_1 = U^{'} \Lambda_1 U^{'T}, S_{2+\cdots+i} = U^{'}(1 - \Lambda_1) U^{'T}. \tag{10}$$

SM_{n*n}, the spatial matrix of class 1, is composed of the common eigenvector $(U^{'})$, and the whitening transformation matrix (W) is expressed in Eq. (11).

$$SM_{n*n} = U^{'T} W. \tag{11}$$

To extract the features for determining the emotional states, we selected only eigenvector U_m, where $U_m = (U_1, \ldots, U_m, U_{N-m+1}, \ldots, U_N)$, and $m \ll N$. Subsequently, we can obtain the spatial filter matrix, SF_{m*n}. Generally, an MCSP uses double the number of classes, $(2 * i)$ or $(i(i-1))/2$, to determine m in SF_{m*n}, from multi-class data [37]. However, the optimal coefficients for extracting the features in correspondence to the emotional state are unknown.

C. Evr-Based Mcsp

We use the EVR [38] to determine the number of spatial filter coefficients necessary to distinguish the emotional states in the EEG data. The EVR can be calculated from the eigenvalues, which determine the magnitude of the new feature space. Specifically, the EVR can reveal how much information can be attributed to each of the components. We apply the EVR to the mixed-covariance matrix of all the classes, to determine the number of spatial matrices required for extracting the best features. Specifically, the mixed-covariance matrix of the multi-class data was computed as expressed in Eq. (5), and the eigen-decomposition was conducted, as expressed in Eq. (6). It is composed of diagonal elements D_{n*1} from diagonal matrix Λ, which is calculated in Eq. (6). The sum of the magnitudes of the entire data is calculate as follows:

$$E = \sum_{j=1}^{n} D. \tag{12}$$

In the subsequent step, we calculate the cumulative value, CV_d, of the diagonal elements, D_{n*1}, to extract only the major features, and compute the accumulative magnitude, E_{cv}, using Eq. (13).

$$E_{cv} = CV_d / E \tag{13}$$

Subsequently, to determine the features that can reduce the dimension of the data, we obtain the spatial filter coefficient, m, as expressed in Eq. (14).

$$m = \sum (E_{cv} < EVR) + 1. \tag{14}$$

In this paper, we use the EVR for obtaining the number of optimal features, and the EVR is set as 90%. The spatial filter matrix for the feature extraction that can identify the emotional state is written in Eq. (15).

$$SF_{m*n} = U'^{T}_{n*m} W_{n*n}. \tag{15}$$

SF_{m*n} apply to the EEG data, X_i. Subsequently, we obtain a new signal, Z_i, projected by the spatial filter as follows:

$$Z_i = SF_{m*n} X_i, \tag{16}$$

where X_i consists of $n * t$.

In summary, we employed the EVR so as to automatically determine the spatial filter coefficients for the MCSP method. The proposed *AsEmo* method uses a subject-independent classification approach that does not require retraining for analyzing the new data. The proposed algorithm is presented in Algorithm 1.

Algorithm 1: The **AsEmo** Algorithm Automatically Determines the Number of Spatial Filters Using an EVR on the Subject Dataset.

Input: Emotion EEG data setX_i
//i is a class label in subject dataset, X is an $n * t$ matrix, n is the number of channels, and t is the time sample.
Output: Spatial filter matrix SF_{m*n}
1: $c_i \leftarrow cov(\sum_{k=1}^{K} X_i)$
// Compute the covariance matrix depending on the class.
2: $C_i \leftarrow sum(c_i/trace(c_i))$
// Compute the normalized covariance matrix depending on the class.
3: $C \leftarrow C_1 + \cdots + C_i$
// Compute the mixed-covariance matrices of all the classes.
4: $U_0 \quad and \quad \Lambda \leftarrow eigen - decomposition(C)$
// U_0 is an $n * n$ unitary matrix of the eigenvectors and Λ is an $n * n$ diagonal matrix of the eigenvalues.
5: $m \leftarrow EVR(\Lambda)$
// Determine the spatial filter coefficient, m, using the EVR in Eqs.(12)–(14).
6: $W \leftarrow \Lambda^{-\frac{1}{2}} U_0^T$
// Compute the whitening transformation matrix.
7: **for** *1* to the number of class *i* **do**
8: $U^{'} \leftarrow$ Eqs. (8)–(10)
// Compute the common eigenvectors, $U^{'}$, of the whitened matrix, S_i.
9: **end for**
10: $SF_{m*n} \leftarrow U'^{T}_{n*m} W_{n*n}$
// Project spatial matrix by $U^{'}_{n*m}$ using the spatial filter coefficient, m.

IV. Experimental Results

A. Data Description

In this paper, we used the DEAP [39] and SEED databases [40] to test the efficiency of the proposed method. For the DEAP data, 32 subjects (50 percent females) were shown 40 music videos, and their physiological signals were recorded. The data of each subject comprised 40 trial datasets, corresponding to the number of music videos, and each dataset rated an emotion of a subject (valence, arousal, liking, and dominance) from one to nine. The DEAP experimental data only comprised EEG signals, excluding electrooculogram (EOG), electromyography (EMG), galvanic skin response (GSR), and temperature. Each experimental dataset had a length of 63 s and was sampled at 128 Hz from 32 channels (32 subjects $\times$ 40 trials $\times$ 32 channels $\times$ 63 s).

We classified the emotional states into four classes using the valence-arousal (VA) plane, as seen in Fig. 1. The gap between two classes was divided by discarding the VA rating values between 4.8 and 5.2, as in [41]. In Fig. 1, the high-valence low-arousal (HVLA) region in the below-right, corresponds to the emotion of calmness. The low-valence and low-arousal

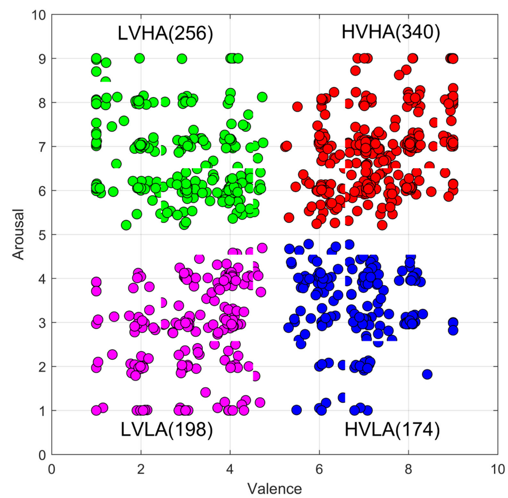


Fig. 1. Valence–arousal plane of the DEAP dataset.

TABLE I
EEG DATA USED IN THE EXPERIMENT

EEG data set	No. of subjects	No. of total trials	No. of channels	Time length	No. of classes
DEAP set	32	968	32	63 ms	4
SEED set	15	675	62	240 ms	3

(LVLA) region in the below-left, denotes the emotion of sadness. The high-valence high-arousal (HVHA) region in the above-right, signifies the emotion of happiness. The low-valence high-arousal (LVHA) region in the above-left of the figure, corresponds to the emotion of fear [42].

For the SEED data, 15 subjects (7 men and 8 women) were shown 15 Chinese film clips (positive, neutral, and negative emotions) of 4 min, and their EEG signals were recorded for each clip. To explore the neural signatures and stable patterns across sessions and individuals, each subject performed the experiment thrice with an interval of approximately 1 week. One experiment contained the EEG data of 15 trials. Therefore, the data of each subject was composed of 45 trials, which were down-sampled with 200 Hz from 62 channels (15 subjects $\times$ 45 trials $\times$ 62 channels $\times$ 4 min). The emotional states in the SEED data were classified into three types (negative, neutral, and positive), which the subjects determined themselves after watching each 4-min clip.

Table I summarizes the details of the two emotion EEG datasets used in the experiment. The DEAP EEG data, as summarized in Table I, were categorized into 4 classes by the VA plane and used in 968 trials among the 1280 trials of the 32 subjects. Specifically, LVHA, HVHA, LVLA, and HVLA used 256, 340, 198, and 174 trials, respectively. The SEED data comprised 225 trials in each class (negative, neutral, and positive) in the experiment. For the experiments, we used two preprocessed EEG data provide by [39] and [40], respectively.

B. Careful Feature Extraction

To classify the emotional states from the multi-class EEG data, we determined the number of optimal spatial filters, i.e., the number of features, by reflecting the EVR in the data. Table II shows the number of spatial filters extracted by the EVR and the classification accuracy measured using the extracted features. We used a multi-SVM algorithm with radial basis kernel functions (RBFs), for measuring the classification accuracy. Recently, deep learning methods, such as deep neural networks, have been applied for classification training in image and video, speech recognition, and natural language processing [43]–[45]. However, deep learning should consider numerous parameters such as number of layers, number of units in the hidden layer, learning rate, and initializing weights during the training, and it should also be increasing the number of training samples in proportion to the number of parameters [21]. Therefore, we used a multi-SVM with an RBF as a classifier that can achieve a good performance with a small number of training samples in the machine learning models.

Using the experimental data, we compared and analyzed the classification accuracy ratio by applying EVRs of 80%, 85%, 90%, and 95% to select the best features. The classification processing was performed by the leave-one-subject-out cross-validation. Specifically, certain subject data selected from the entire subject dataset were used as the testing data, and the remaining dataset was employed as the training dataset. The classifier was trained using the extracted features from the training data. As a result, in the case of the DEAP data listed in Table II, the highest classification accuracy was 82.25 $\pm$ 5.39% and the number of spatial filters was 11.9 when an EVR of 95% was employed. For the SEED data, the highest classification accuracy was observed at an EVR of 90%, and the number of spatial filters averaged at 6.5. Generally, the feature with the highest average value and the lowest standard deviation performed the best. In this paper, we used an EVR of 90% to ensure high classification accuracy and low standard deviation for both the DEAP and SEED data simultaneously.

In this paper, we apply the EVR of 90% on MCSP that was selected for extracting the optimal features. A primary MCSP method to multi-class data, the number of classes in the given data or twice the number of classes are passively selected, to determine the number of spatial filters. Wentrup and Buss [17] determined the number of filters using joint approximate diagonalizations (JADs), suchasindependentcomponentanalysis(ICA), for the classfication of multi-class data. Blankertz *et al.* [46] proposed to use spatial filters by determining a common basis for the classes, and Lotte [47] determined the number of filters using a waveform length optimal spatial filter (WOSF). We analyzed and compared the proposed EVR method to the three above-mentioned existing methods, to determine the number of filters.

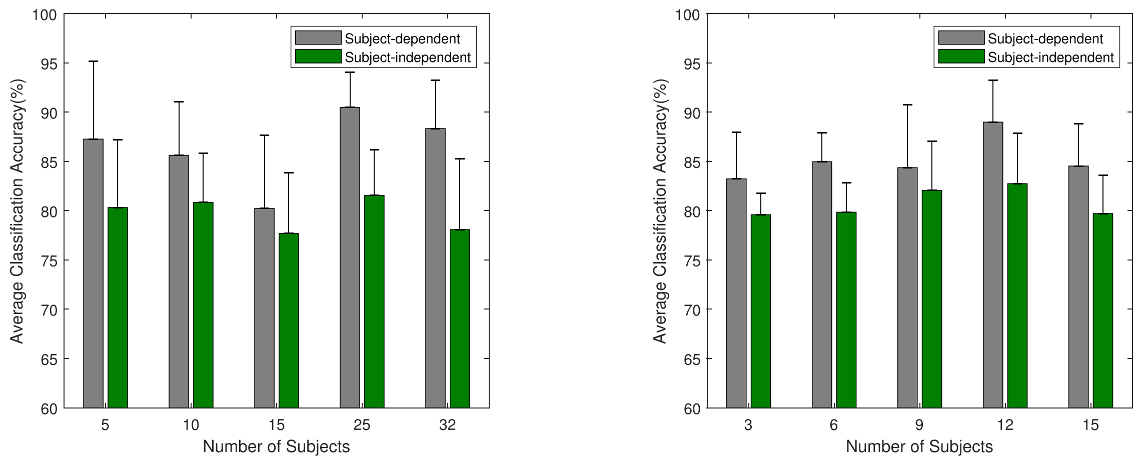
Table III shows the classification accuracy and standard deviation of the data obtained with the number of filters extracted by *AsEmo* and the existing methods. Consequently, Wentrup and Buss [17] achieved average classification accuracies of 64.90 $\pm$ 4.81% and 55.05 $\pm$ 3.90% when the number of features

TABLE II
NUMBER OF SPATIAL FILTERS AND CLASSIFICATION ACCURACY DETECTED USING *ASEMO*

EVR	DEAP Data(4-class)			SEED Data(3-class)		
	Average Spatial filters	Average accuracy(%)	Standard deviation	Average Spatial filters	Average accuracy(%)	Standard deviation
80%	8.5	79.94	±11.10	4.9	78.96	±4.18
85%	10.1	80.41	±7.61	5.7	78.78	±5.63
90%	10.5	82.24	±**4.35**	**6.5**	**81.30**	±**3.73**
95%	**11.9**	**82.25**	±5.39	8.9	79.12	±4.79

TABLE III
COMPARISON OF *ASEMO* AND EXISTING METHODS FOR DETERMINING SPATIAL FILTERS FOR FEATURE EXTRACTION

Data	Subject	*AsEmo* (EVR: 90%)		Wentrup et al. [17]		Blankertz et al. [46]		Lotte [47]	
		Num. Feature	Accuracy(%)	Num. Feature	Accuracy(%)	Num. Feature	Accuracy(%)	Num. Feature	Accuracy(%)
DEAP Data	1	12	87.21	8	63.84	8	63.09	16	73.66
	2	10	89.47	8	64.31	8	64.10	16	74.95
	3	10	87.93	8	75.25	8	45.62	16	64.28
	4	11	71.48	8	72.89	8	60.67	16	86.19
	5	10	82.60	8	65.82	8	60.44	16	80.63
	6	12	93.39	8	66.09	8	64.78	16	75.23
	7	12	86.36	8	69.83	8	49.49	16	85.85
	8	10	88.94	8	63.71	8	67.80	16	70.44
	9	11	87.15	8	60.31	8	76.39	16	78.49
	10	11	81.31	8	71.77	8	60.32	16	77.79
	11	10	89.96	8	57.99	8	60.09	16	80.60
	12	12	87.15	8	67.96	8	59.66	16	80.56
	13	11	88.71	8	64.26	8	74.26	16	74.68
	14	9	77.24	8	58.32	8	55.61	16	70.85
	15	11	81.53	8	71.30	8	68.59	16	78.18
	16	10	84.98	8	60.31	8	70.53	16	82.14
	17	10	82.84	8	67.98	8	54.95	16	84.47
	18	10	76.30	8	63.30	8	71.67	16	84.55
	19	10	85.07	8	65.32	8	65.24	16	74.68
	20	11	88.41	8	64.06	8	62.65	16	79.39
	21	11	85.42	8	58.59	8	63.73	16	72.93
	22	10	83.62	8	71.06	8	76.93	16	73.43
	23	10	78.93	8	63.97	8	66.20	16	78.97
	24	10	79.82	8	58.56	8	72.88	16	86.66
	25	11	80.46	8	67.15	8	71.25	16	75.15
	26	10	77.16	8	64.09	8	65.56	16	80.86
	27	12	92.04	8	55.95	8	67.86	16	77.87
	28	11	87.62	8	61.85	8	53.50	16	84.59
	29	10	77.62	8	60.66	8	59.76	16	73.55
	30	12	87.23	8	70.85	8	61.74	16	79.16
	31	10	87.39	8	66.85	8	69.32	16	81.76
	32	11	84.14	8	63.92	8	61.88	16	84.50
Average		10.7	**84.20**	8	64.90	8	63.96	16	78.34
STD		-	±5.04	-	±**4.81**	-	±7.32	-	±5.27
SEED Data	1	7	86.32	6	58.30	6	59.63	12	79.07
	2	8	88.71	6	61.16	6	43.68	12	77.21
	3	6	78.94	6	55.44	6	46.19	12	82.25
	4	7	80.79	6	57.58	6	52.54	12	77.10
	5	9	88.88	6	55.24	6	48.40	12	75.37
	6	6	80.77	6	56.84	6	66.85	12	79.50
	7	8	82.68	6	49.66	6	60.12	12	72.85
	8	8	85.99	6	59.54	6	40.94	12	75.70
	9	5	73.74	6	47.57	6	34.39	12	70.51
	10	6	81.88	6	51.71	6	61.01	12	76.73
	11	8	82.01	6	53.12	6	52.62	12	73.00
	12	8	81.91	6	50.37	6	62.67	12	71.33
	13	8	83.36	6	57.07	6	44.65	12	73.61
	14	8	83.66	6	58.00	6	56.38	12	71.04
	15	6	81.04	6	54.26	6	44.68	12	70.24
Average		7.1	**82.71**	6	55.06	6	51.65	12	75.03
STD		-	±3.83	-	± 3.90	-	±9.31	-	±**3.63**



(a) DEAP data (b) SEED data

Fig. 2. Classification accuracy based on the subject-dependent and subject-independent methods.

extracted were eight and six for the DEAP and SEED data, respectively. The method proposed by Blankertz *et al.* [46] extracted eight and six features from the DEAP and SEED data and achieved classification accuracy of 63.96 $\pm$ 7.32% and 51.65 $\pm$ 9.31% with the extracted features, respectively. Lotte's method [47] presented average classification accuracies of 78.34 $\pm$ 5.27% and 75.03 $\pm$ 3.63% using the 16 and 12 extracted features from the DEAP and SEED data, respectively. Among all these methods for determining the number of filters, Lotte's method [47] which determines the number of filters based on the wavelet length, demonstrated the best performance. In comparison, our proposed method achieved an average accuracy of 84.20 $\pm$ 5.04% and 82.71 $\pm$ 3.83% when applying 10.7 and 7.1 extracted average features from the DEAP and SEED data, respectively. Thus, our method improved the classification accuracy by 6% and 7% for the DEAP and SEED data, respectively, compared to the method developed by Lotte. Therefore, the proposed feature extraction method, which determines the number of spatial filters based on the EVR, performs better at classifying emotional states than the existing methods.

C. Effectiveness

The EEG data are real-time data, and their associated application programs generally use processes that provide services to users using real-time analyzed results. Therefore, the subject-independent methods are suitable for EEG-based applications, which is recommended for the instantaneous feedback systems. For verifying the effectiveness of the subject-independent method, we compared the classification accuracy between the subject-independent and subject-dependent methods. Fig. 2 shows the average classification accuracy of a subject-independent method capable of real-time processing and a subject-dependent method, which is primarily used in emotion EEG research. In this paper, a subject-independent method is employed by leave-one-subject-out cross-validation, and the subject-dependent method adopts a ten-fold cross-validation on the one subject data.

In Fig. 2, the result of the DEAP data is shown on the left side and that of the SEED data is shown on the right. The x-axis indicates the number of subject data. That is, in the subject-independent case, if Subject 1 data is test data, the remaining data set(from Subject 2–5) is training data. If Subject 2 data is the test data, then Subject 1, 3, 4, and 5 datasets are used for training. In this way, five indicates the use of five subject datasets as test data. In contrast, five in the subject-dependent method means that a five subject dataset performs ten-fold cross-validations. Therefore, the y-axis represents the average classification accuracy measured with the increase in the number of subjects. The subject-dependent method presents a higher average accuracy than the subject-independent method, as can be seen from Fig. 2. Thus, the subject-dependent method can provide a higher accuracy than the subject-independent method. However, the subject-dependent method poses a disadvantage retraining is required for new data each time when new data are entered in the system as the testing data. Therefore, the subject-independent method is more suitable for EEG data than the subject-dependent method, which requires real-time processing.

This paper proposed *AsEmo* as a method to well-classify the emotional state from complex and varied emotional states, i.e., multi-class emotion EEG data. To verify the performance of *AsEmo*, we compared the proposed method to typical existing methods for identifying multi-class emotion EEG data, such as MCSP, hybrid adaptive filter-HOC (HAF-HOC), and mRMR. Table IV shows the performance comparison of the existing methods and our proposed method for multi-class data. We adopted the leave-one subject-out cross-validation, which was trained on 31 subjects and tested on the remaining subjects for the DEAP data. For the SEED data, 14 subjects were used for training and the remaining subjects were used for testing. In this experiment, a subject data for test data was selected randomly, but test data was never overlapped. We evaluated the performance using the accuracy averaged over all the test subjects in the DEAP and SEED data. As can be seen from Table IV, we repeatedly ran ten-task and measured the averaged accuracy.

TABLE IV
COMPARISON OF MULTI-CLASS CLASSIFICATION ACCURACY OBTAINED VIA *ASEMO* AND STATE-OF-THE-ART FEATURE EXTRACTION METHODS

Data	No.Task	MCSP[17]		HAF-HOC[18]		mRMR[19]		*AsEmo* (90%)	
		Num.Fea	Accuracy(%)	Num.Fea	Accuracy(%)	Num.Fea	Accuracy(%)	Num.Fea	Accuracy(%)
DEAP	Task 1	8	60.91	55	59.13	35	79.95	9	85.05
	Task 2	8	63.30	55	55.53	35	81.33	10	82.47
	Task 3	8	62.15	55	56.18	35	79.40	10	87.41
	Task 4	8	64.86	55	58.28	35	83.27	8	88.89
	Task 5	8	62.11	55	58.54	35	78.46	11	80.19
	Task 6	8	65.67	55	55.36	35	84.99	10	80.47
	Task 7	8	63.12	55	56.69	35	71.30	11	79.58
	Task 8	8	71.31	55	56.44	35	80.81	10	83.45
	Task 9	8	59.62	55	60.24	35	80.66	10	82.61
	Task 10	8	58.97	55	59.48	35	91.62	11	82.76
	Average(STD)	8	63.20(±3.54)	55	57.59(±1.75)	35	81.18(±5.14)	10.0	83.29(±3.06)
SEED	Task 1	6	58.90	55	52.46	35	74.31	6	79.58
	Task 2	6	61.23	55	55.86	35	70.89	6	85.93
	Task 3	6	60.45	55	54.01	35	76.05	7	88.65
	Task 4	6	58.06	55	51.56	35	73.02	7	79.73
	Task 5	6	61.03	55	56.99	35	74.71	8	85.97
	Task 6	6	51.18	55	57.94	35	73.45	6	83.96
	Task 7	6	64.48	55	63.07	35	71.26	8	80.09
	Task 8	6	64.27	55	60.30	35	74.98	6	76.34
	Task 9	6	59.53	55	47.76	35	75.03	6	77.76
	Task 10	6	64.42	55	42.54	35	74.15	7	80.19
	Average(STD)	6	60.36(±3.98)	55	54.25(±6.04)	35	73.79(±1.66)	6.7	81.82(±4.04)

Among the existing feature extraction methods for multi-class data, the MCSP extracted eight and six features and achieved classification accuracies of 63.20(± 3.54)% and 60.36(± 3.98)% on the DEAP and SEED data, respectively. The HAF-HOC presented classification accuracies of 57.59(± 1.75)% and 54.25(± 6.04)% using a 55-feature set, and mRMR achieved average classification accuracies of 81.18(± 5.14)% and 73.79(± 1.66)% with a 35-feature set for the DEAP and SEED data, respectively. The mRMR method presented the highest classification accuracy on both the DEAP and SEED data among the existing feature extraction methods. However, in comparison to *AsEmo*, its accuracy was lower by approximately 2% and 8% on the DEAP and SEED data, respectively. *AsEmo* used the EVR of the multi-class covariance matrix to automatically determine the optimal number of spatial filters that can distinguish emotional states as well as applied a subject-independent method for the rapid analysis of new data without classifier re-training. Thus, the proposed method can ensure a better result than the existing feature extraction methods in multi-class emotion EEG data analysis.

D. Applicability

The proposed *AsEmo* method presents good performance in terms of both quality of feature extraction and multi-class data classification. Additionally, our method also demonstrates high classification performance for the feature extraction of binary-class data. Fig. 3 shows the performance result between our proposed method with the existing methods (PSD, STFT, DWT, and CSP) for emotional state classification based on binary-class EEG data. The existing methods are representative feature extraction methods that are typically used most frequently in emotion recognition studies based on EEGs [31].

For measuring the classification accuracy of binary-class data, the DEAP data utilized LVLA- and HVHA-class data, while the SEED data utilized positive- and negative-class data. The PSD method performed classification training by extracting 320 (i.e., 10 PSD-bandwidths for 32 EEG channels) and 640 variables for the DEAP and SEED data, respectively. The STFT method used 128 (i.e., theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz). and gamma (30–50 Hz) for 32 EEG channels) and 248 variables for the DEAP and SEED data, respectively. The DWT method extracted 96 (32 EEG channels over 6 bands) and 372 variables for the DEAP and SEED data, respectively. The CSP used eight and six features for classification training. Consequently, the PSD [12] exhibited the highest classification accuracy as compared to STFT [10], DWT [13], and CSP [16]. However, compared to the PSD method, the proposed method achieved higher accuracies of 14.4% for the DEAP data and 12.3% for the SEED data, thereby proving it had the highest classification accuracy among all considered feature extraction methods.

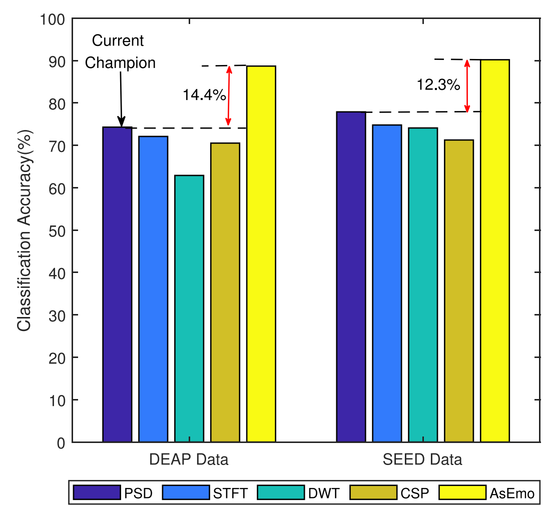
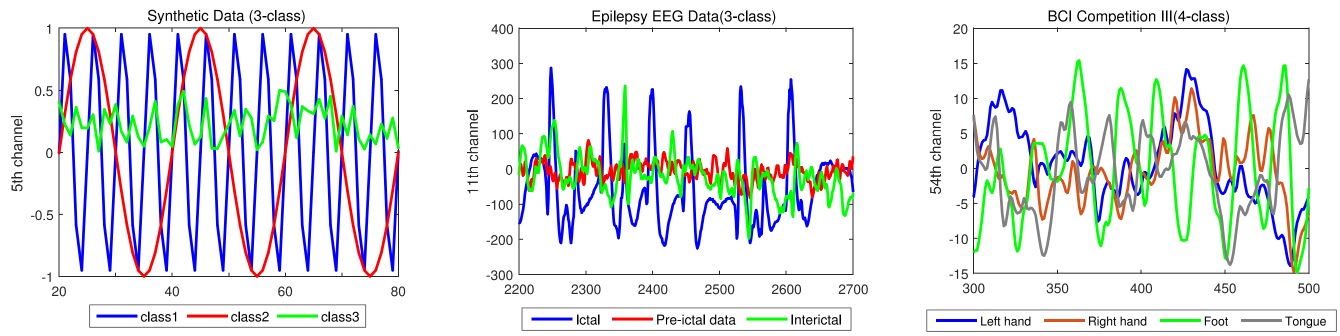


Fig. 3. Classification accuracy for the binary-class data.



(a) Synthetic data (b) Epilepsy EEG data (c) BCI competition III

Fig. 4. Original synthetic data, epilepsy EEG data, and motor imagery.

TABLE V
CLASSIFICATION ACCURACY FOR SYNTHETIC, EPILEPSY EEG, AND BCI COMPETITION III DATA

Data	*i*-class					
	MCSP[17]		mRMR[19]		*AsEmo*	
	Num.Fea	Accuracy(%)	Num.Fea	Accuracy(%)	Num.Fea	Accuracy(%)
Synthetic	6	72.50	45	79.94	6	85.89
Epilepsy[48]	6	67.73	45	72.61	8	78.59
BCI Competition III[49]	8	72.27	45	74.56	9	80.13

One of the advantages of the proposed method is its applicability to a variety of real-time data. To verify this applicability of the proposed method, we extracted features by applying (a) synthetic data that were randomly generated, (b) epilepsy EEG data [48], and (c) motor imagery data [49], as depicted in Fig. 4. The synthetic data were composed of three classes, as presented in Fig. 4(a), and two of these classes had main periodicities of 20 and 3; the remaining class was created by randomly adding Gaussian white noise. Epilepsy EEG data were obtained from the "Epilepsy Center of the University Hospital of Freiburg [48];" these were real-time three-class data comprising ictal, inter-ictal, and pre-ictal phases. The BCI competition III data were EEG data obtained from four types of motor imageries(left hand, right hand, foot, and tongue) from nine subjects. Table V lists the number of extracted features from three types of time series data (Fig. 4) and the classification accuracy. We compared these results with those of two existing methods: MCSP and mRMR. The results indicated that the *AsEmo* method achieved a classification accuracy that was approximatively 5% higher than that of the mRMR method. Thus, *AsEmo* offers sufficient applicability as a feature extraction method for real-time epilepsy and motor imagery data, as well as EEG signal data for emotional state recognition.

V. Discussion

Emotion recognition via feature extraction and classification using EEG data is considered as the primary issue. Feature extraction is process to obtain clearly distinguishable features for facilitating EEG data classification. Classification involves a series of processes that confirms the obtained result using a model matched with actual EEG data. For emotion recognition, the method extracting the optimal features, or method combining the extracted features with a classifier for providing the best classification accuracy is typically considered as the primary goal.

The technology to extract features for recognizing EEG-based emotional states is undergoing continuous developments, which were initiated by studies that classified and extracted features from binary-class data, such as positive and negative [50], valence and arousal [51], fear and relaxation [10], and happy and unhappy [12] data. However, feature extraction methods for binary-class data cannot typically be applied to multi-class data. Even if this is achieved, a considerable degradation in performance is observed [29].

For multiclass data, various feature extraction methods are being developed, leading to continuously improving performance. The MCSP [17] and HAF-HOC [18] methods are used for comparison in this paper; these methods were proposed for extracting features from multi-class EEG data. Although MCSP extract more smaller features than *AsEmo*, they exhibit a 20–27% reduction in performance. On the other hand, mRMR [19] exhibited a higher classification accuracy than the abovementioned two methods. Nevertheless, mRMR requires considerably more training time than *AsEmo* because it extracts and uses a larger number of features.

Feature extraction is an important phase for the configuration of all types of pattern classification; it establishes new valuable information from raw data by reformatting, combining, and transforming the primary features. Such feature extraction has been developed in various fields such as machine learning, pattern recognition, image processing, and signal processing. These developed feature extraction methods have been applied to various application systems. In this paper, we focused on the emotion state recognition process with the aim of improving classification accuracy. Specifically, for extracting features that can well-classify the emotional state, we proposed the *AsEmo* method, which determines number of optimal features from emotion EEG data. Our method achieved the better performance than existing methods in terms of emotion EEG data as well the Epilepsy [48] and BCI competition III [49]data. In addition, *AsEmo* adopts a subject-independent method that employs real-time processing. Therefore, the proposed method, *AsEmo*, is suitable for analyses of real-time data of physiological signals and is particularly advantageous for real-time data analysis systems, such as the one based on EEGs.

VI. Conclusion

In this paper, *AsEmo* was proposed as a feature extraction method for classifying various emotional states based on EEG data with non-linear and non-stationary properties. The proposed method could automatically determine the number of optimal MCSP spatial filters by applying an EVR to the covariance values of all class data and could also extract the features that could well-identify emotional states. In addition, it was useful for the analysis of new data, owing to the application of a subject-independent method that could be employed for real-time analyses. *AsEmo* achieved a classification accuracy of up to 2–8% higher than those of existing emotion classification methods in terms of the extracted best features and classification learning based on subject-independence. Further research is necessary to elucidate real-time applications via the implementation of an on-line feedback system whereby the analysis and processing of various data are possible.

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