The brain feature extractor in Fig. 1 analyzes the signals to extract the necessary features for the mood classification. EEG signals are typically described in terms of rhythmic activity. The rhythmic activity is divided into bands by frequency. The majority of the cerebral signals observed in a scalp EEG are in the range of 1-20Hz according to standard clinical recording techniques [5]. The EEG sampling rate of the emotive EPOC is 128Hz/s [1]. The window length for the 512-point FFT of the received EEG data is eight seconds, and the frame shift is 8.7ms [6]. In the band cluster of the brainwave feature extractor, the power spectra of the EEG data are grouped in five frequency bands, as indicated in [7].

In the process of feature extraction, $p$ and $t$ denote a pin index and a window index. $E_{t,p}$ is defined as the $d$ band energy in the $t$-th window from the $p$-th pin. $f_{v_i}^p$ is the set of the five band energies from the $1$ pins in the $t$-th window - the dimension is $70$. The proposed EEG mood classifier gathers $f_{v_i}^p$ for 15 seconds while a user listens to a music clip. $FV$ for a

---

**Fig. 1 Process of mood classification using EEG. (Brain feature extractor -> Brainwave feature extractor)**

Due to the smearing effect of the skull, the underlying source signal is spread over several channels. In the RCSP filter, the EEG signals are estimated to reduce the diffusion from the spatial activity among the signals. The RCSP filter encodes the most discriminative information from multiple signals [4].

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song is separated with 1.724 f

, which are based on an eight second window and 8.7ms frame shift . Each f

 is classified as a ’positive’ or ’negative’ mood class using the user’s personal mood model. Mood-classification results for a music clip are counted and the EEG music recommender determines the dominant emotional mood as the most frequently counted mood for the music clip. The set of feature vectors FV is presented as:

\[ FV = \{ f_{v1}, \ldots, f_{v\ell}, \ldots, f_{vJ} \} \]

\[ f_{vi} = (E_{ai,1}, E_{ai,2}, E_{ai,3}, E_{ai,4}, E_{ai,5}, E_{ai,6}, E_{ai,7}, E_{ai,8}, E_{ai,9}, E_{ai,10}, E_{ai,11}, E_{ai,12}, E_{ai,13}, E_{ai,14}, E_{ai,15}, E_{ai,16}) \]  

(1)

B. RCSP Filter based EEG Signal Estimation

Because of the low spatial resolution of EEGs, spatial filtering can be used to facilitate the extraction of the useful features for BCI classification. Common Spatial Pattern (CSP) is a supervised method to find spatial filters. CSP based filters still show the sensitivity to noise and overfitting from the applied samples. To overcome this sensitivity, this paper applies Regularized CSP (RCSP) among the several CSP variants [4].

\( \bar{S}_i \) is an EEG signal matrix for class \( i \), with EEG channels in columns and time samples in rows. An average spatial covariance matrix of \( \bar{S}_i \) is represented by \( C_i \), \( i \in \{ 1, 2 \} \). In this paper, classes are assigned with a positive and a negative emotion. To find CSP based filters, a spatial filter \( \hat{w} \) is determined by (2).

\[ \hat{w} = \arg \max_{w} \left( \frac{w^T C_i w}{w^T C_i w + \alpha w^T I w} \right) \]

(2)

The maximization problem in (2) is solved as a generalized eigenvalue problem. The eigenvector \( w \) corresponding to the maximum eigenvalue is the direction vector. This direction vector \( w \) is a spatial filter for \( S_i \) and \( w^T \) is called a common spatial pattern for \( S_i \). RCSP uses a regularization framework to penalize undesired solutions by two user-defined regularization parameters. This paper applies Tikhonov Regularization CSP algorithm [7], which is expressed as:

\[ \hat{w}_t = \arg \max_{w} \left( \frac{w^T C_i w}{w^T C_i w + \alpha w^T I w} \right) \text{ with } \bar{C}_i = (1-\beta) C_i + \beta I \]

(3)

Where \( \bar{C}_i \) is the regularized \( C_i \), and \( I \) is a identity matrix whose size is \( N \) by \( N \). In this process, \( \alpha \) and \( \beta \) are user-defined regularization parameters (\( 0 \leq \alpha, \beta \leq 1 \)). \( \hat{w}_t \) is a common spatial pattern for \( S_t \). \( \hat{S}_t \) is the input of FFT module in brain feature extractor in Fig. 1.

\[ \hat{S}_t = \hat{w}_t^T S_t \]

(4)

III. EXPERIMENTS

This section presents the performance evaluation of the EEG mood classifier by measuring the accuracies. Two kinds of EEG evaluation datasets for mood classification, DEAP and KETI EEG datasets, were used. The accuracies in Table I were measured using a ten-fold cross validation method.

The proposed system achieved an accuracy rate of 83.02%. When using the RCSP spatial filter before the SVM classifier, there was a remarkable improvement in the performance. The EU FP7 PetaMedia project reported an accuracy of 70.25% [8].

<table>
<thead>
<tr>
<th>System</th>
<th>Feature</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>14-pin</td>
<td>65.63</td>
</tr>
<tr>
<td>RCSP-SVM</td>
<td>14-pin</td>
<td>68.89</td>
</tr>
<tr>
<td>EU FP7 PetaMedia</td>
<td>32-pin + physiological</td>
<td>82.4</td>
</tr>
<tr>
<td></td>
<td>/ audio/visual features</td>
<td></td>
</tr>
<tr>
<td>KETI EEG</td>
<td>SVM</td>
<td>70.25</td>
</tr>
<tr>
<td></td>
<td>14-pin after RCSP</td>
<td>83.02</td>
</tr>
</tbody>
</table>

IV. CONCLUSIONS

In this paper, mood classification using user brainwaves is proposed. The proposed RCSP based algorithms achieved an overall accuracy of 83.02% in the binary mood classification for the KETI AFA2000 music corpus. The performance of the proposed method was higher than one of the best EEG-based mood-classification systems, despite only using audio stimuli.

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References