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Single-Trial EEG-based Emotion Recognition Using Kernel Eigen-Emotion Pattern and Adaptive Support Vector Machine

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Abstract— **Single-trial electroencephalography (EEG)-based emotion recognition enables us to perform fast and direct assessments of human emotional states. However, previous works suggest that a great improvement on the classification accuracy of valence and arousal levels is still needed. To address this, we propose a novel emotional EEG feature extraction method: kernel Eigen-emotion pattern (KEEP). An adaptive SVM is also proposed to deal with the problem of learning from imbalanced emotional EEG data sets. In this study, a set of pictures from IAPS are used for emotion induction. Results based on seven participants show that KEEP gives much better classification results than the widely-used EEG frequency band power features. Also, the adaptive SVM greatly improves classification performance of commonly-adopted SVM classifier. Combined use of KEEP and adaptive SVM can achieve high average valence and arousal classification rates of 73.42% and 73.57%. The highest classification rates for valence and arousal are 80% and 79%, respectively. The results are very promising.**

I. Introduction

Since the discovery that the frontal asymmetry of electroencephalography (EEG) based signals can help differentiate between positive and negative emotions [1]-[2], EEG-based emotion recognition has been a critical to-be-solved issue in many research fields ranging from developing a human-centered human-computer interface to an emotion monitoring system in the health care contexts. However, emotion recognition is a highly complex and difficult pattern recognition problem [3], especially when EEG signals are the only system input type and other commonly-used neurophysiological measures (skin conductance, electrocardiogram, blood pressure) are ignored [17]. Thus, many labs have recently attempted to solve the problem of EEG-based emotion recognition by proposing various methods [6]-[17].

Discrete emotion [4],[5] and the bi-dimensional emotion [2] models have been widely adopted to operationally define the scope of emotions. In discrete emotion models, several emotion types including anger, fear, happy, sadness, disgust and surprise are commonly identified as basic emotions [4], [5]. In contrast, the bi-dimensional model categorizes emotional states in a 2-D feature space spanned by valence and arousal, which results in four emotional categories: high-valence-high-arousal (HVHA), low-valence-high-arousal (LVHA), low-valence-low-arousal (LVLA), and high-valence-low-arousal (HVLA). Methods based on discrete emotion models aimed at classifying a set of discrete emotional states [6]-[11], while methods based on the bi-dimensional model aimed to solve two kinds of binary classification problems for valence (pleasant vs. unpleasant) and arousal levels (high vs. low activation) [12]-[17].

TABLE I. Previous EEG-based Works on Emotion Classification

Ref.	Tasks	CR (%)
[6]	happy, sad	93.25
[7]	happiness, surprise, anger, fear, disgust, sadness	88.33
[8]	anger, boredom, confusion, contempt, curious, disgust, eureka, frustration	82.27
[9]	joy, anger, pleasure, sad	75.97
[10]	joy, sad, neutral	74
[11]	joy, relax, sad, fear	66.51
[12],[13]	valence classification, arousal classification	32 and 37
[14]	valence classification	47.11
[15]	valence classification	66.7
*[16]	valence classification, arousal classification	90 and 85
*[17]	valence classification, arousal classification	92.8 and 89.2

*non-single trial study

Current literature suggests that the classification r is better for the discrete emotion models [6]-[11] than the bi-dimensional emotion model [12]-[15]. Despite the difference of definition, the emotional states defined in the discrete emotion models can be located within the valence-arousal space in the bi-dimensional emotion model. For example, both “angry” and ”disgust” fall into the same category - LVHA. In valence classification, both HVHA and HVLA belong to the positive class while LVHA and LVLA belong to the negative class. Since each of the two classes includes multiple discrete emotional states, EEG patterns of each class are inherently distributed with a much larger variation than those of a single discrete emotion in the space of patterns. Thus, despite that various factors (e.g., gender, experience of subjects, electrode layout, type of emotional stimulus, length of EEG epoch, signal processing, extracted features, classifier design) can influence the EEG-based emotion recognition accuracy, the valence or arousal classification [12]-[15] generally resulted in poorer accuracy than the classification between discrete emotional states [6]-[11](Table I).

Both valence and arousal classification are critical in developing an emotion recognition system to evaluate and even monitor the emotional states of people with affective disorders. The valence classification allows for a direct approach for negative emotion (low-valence) detection, and the arousal classification further evaluate the activation level (high or low) of the detected negative emotion. Moreover, single-trial EEG-based emotion recognition is more efficient

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and practical for a real-time emotion monitoring system in clinical settings. However, the classification performance of single-trail EEG-based methods [12]-[15] has not been satisfactory (Table I). Hence, the development of more robust algorithms is of urgency and primary importance.

To address this critical issue, we propose a novel EEG feature extraction method - kernel Eigen-emotion pattern (KEEP), and modify the widely-used classifier SVM to be adapted to the imbalanced emotion-EEG data sets. The KEEP is based on EEG frequency band powers and the kernel principal component analysis (kernel PCA) [18]. It not only extracts higher-order statistics across multiple EEG band powers and electrode locations, enabling effective representation of complex emotion-triggered oscillatory brain activity, but also reduces the dimension of input vectors. The adaptive SVM proposed in our lab [21] can achieve better generalization performance than regular SVM and solve the problem of learning from imbalanced EEG data sets, which avoid the so-called class-boundary-skew problem [19]-[20] that would drop the classification performance of regular SVM in emotion recognition. The combined Use of KEEP and the adaptive SVM significantly improve the classification accuracy for both valence and arousal classification.

II. Method

A. Participants

Seven college participants (20~24 y/o) with normal or corrected-to-normal vision participated in this study. All participants have no neurological or psychological medical history. Before experiments, we obtained informed consent from each participant.

B. Apparatus

Stimulus presentation was controlled by a personal computer, which was connected with the EEG recording system. All visual stimuli were presented on a 17-inch CRT screen and subjects were seated on a fixed chair at the position so that their eyes were ～57 cm in front of the display. EEG signals were recorded from 64 electrodes mounted on an electro-cap (Quick-Cap 64, NeuroScan), in which two electrodes were references positioned at bilateral mastoids. Locations of all electrodes follow the international 10-20 system. Impendence of all electrodes was kept below 5 kΩ. Ocular artifacts were monitored by horizontal (HEOR, HEOL) and vertical (VEOH, VEOL) bipolar EOG electrodes for later off-line rejection. Both the EEG and EOG channels were recorded with a band-pass filter of 0.05 to 100 Hz and a gain setting of 1000 using a NuAmps amplifier (NeuroScan, Inc.). Raw EEG signals were digitized with a sampling rate of 500 Hz.

C. Stimuli and Tasks

A set of pictures from International Affective Picture System (IAPS) were used to induce emotions from participants. The pictures in IAPS system were all rated in terms of the perceived valence and arousal levels and were divided into four categories: HVHA, LVHA, LVLA, and HVLA. We selected a pool of 100 pictures with 25 pictures for each category from IAPS. Fig. 1 shows the distribution of some examples of the selected pictures in the 2-D emotion space, where the 2-D coordinate of each point represents the valence and arousal values of a picture.

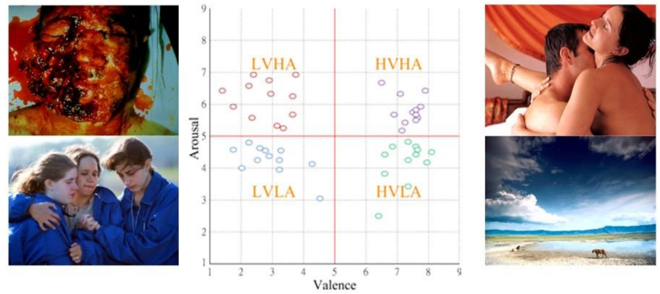

Figure 1. Distribution of examples of the pictures selected from IAPS in the 2-dimensional space spanned by valence and arousal.

D. Emotion-induction Experiment

The emotion-induction experiment (100 trials) is illustrated in Fig. 2. Each trial started with a 2-sec trial-ready cue followed by a 2-sec resting period during which subjects were instructed to passively stare at the center fixation cross and try not to think anything on purpose. Subsequently, a 7-sec picture-display period was presented and participants were instructed to try to engage themselves into the emotion that a given picture may represent. At the end of each trial, participants psychometrically evaluated the perceived emotion and categorized it as one of the four categories in the valence-arousal space. Finally, participants were instructed to press any key on a keyboard after completing the self-assessment task to start the next trial in which a different picture was presented during the picture-display period.

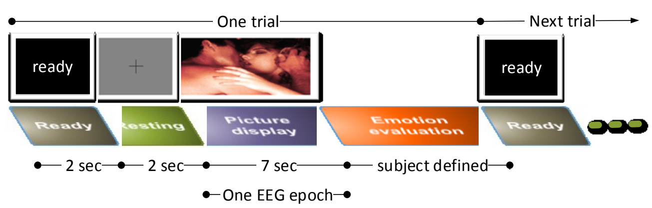

Figure 2. Emotion-induction experiment adopted in this study.

E. Data Labeling

EEG data from all 100 trials were used for single-trial based emotion recognition. EEG segmentation was performed in a time-locked fashion: the 7-sec emotion-induction related EEG epoch of each trial was segmented from the recorded EEG using the stimulus codes that have been embedded into the data stream within each trial. The label of each EEG epoch was determined by participants' subjective psychometric evaluation. Therefore, for a given emotional picture, the induced subjective emotion sometimes did not agree with the original emotion category recorded in IAPS in our study, as has also been reported in [13]. Thus, labels of some EEG epochs were not identical to the pictures' original categories in IAPS. For analyses, the EEG epochs labeled as HVHA and HVLA (HVHA and LVHA) were treated as positive data, and epochs labeled as LVHA and LVLA (HVLA and LVLA) were treated as negative data for valence (arousal) classification. As summarized in Table II, the data sets for either valence or arousal are all imbalanced.

TABLE II. EEG DATA LABELING RESULTS

Participants	Valence classification		Arousal classification	
	# positives	*# negatives*	*# positives*	*# negatives*
P1	38	52	73	27
P2	54	46	68	32
P3	56	44	66	34
P4	51	49	67	33
P5	43	57	57	43
P6	52	48	63	37
P7	56	44	66	34

F. Emotional EEG Feature Extraction based on KEEP

For a 7-sec EEG epoch, five frequency band powers are calculated using Discrete Fourier Transform, including theta (4–8 Hz.), alpha (8–13 Hz.), low beta (13–20 Hz.), high beta (20–30 Hz.) and gamma (30–45 Hz.). The band powers extracted from all 62-channel EEG epochs are concatenated to form an n-dimensional EEG band power (BP) vector $\mathbf{x}$, where n=310. The vector is then sent to kernel PCA for further feature extraction. Kernel PCA method consists of offline training stage and online testing stage.

Training stage. Suppose that a training set $\{\mathbf{x}_i \in R^n\}_{i=1,\dots,M}$ is given, where M is the size of the set. The data are mapped into a higher-dimensional feature space F *via* a nonlinear mapping $\phi : R^n \to F$, and are centered to have zero mean: $\sum_{i=1}^{M}\phi(\mathbf{x}_i) = 0$. Please refer to Appendix B of [18] for details of the mapped-data centering method. Then kernel PCA solves the eigenvalue problem:

$$\lambda \mathbf{v} = \mathbf{C}\mathbf{v} \tag{1}$$

where $\mathbf{C} = 1/M\left(\sum_{i=1}^{M}\phi(\mathbf{x}_i)\phi^T(\mathbf{x}_i)\right)$ is the covariance matrix of the mapped data in F, and $\mathbf{v} \in F$ are eigenvectors associated with nonzero eigenvalues λ. By using the kernel function: $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)\cdot\phi^T(\mathbf{x}_i)$, solving (1) is then equivalent to solving the following eigenvalue problem of the $M \times M$ kernel matrix $\mathbf{K} : K_{ij} \equiv K(\mathbf{x}_i, \mathbf{x}_j)$:

$$M\lambda \mathbf{a} = \mathbf{K}\mathbf{a} \tag{2}$$

for eigenvalues $\lambda_l \neq 0$ and eigenvectors $\mathbf{a}^l = (a_1^l,\dots, a_M^l)^T$ subject to the normalization condition $\lambda_l(\mathbf{a}^l \cdot \mathbf{a}^l) = 1$.

Testing stage. For the purpose of dimensionality reduction, d eigenvectors associated with the first d largest nonzero eigenvalues are chosen as the projection axes such that $d << n$ and $d < M$. For a testing EEG BP vector **x**, its projection onto the kth eigenvector $\mathbf{v}^k$ is computed by

$$z^k = \mathbf{v}^k \cdot \phi(\mathbf{x}) = \sum_{i=1}^{M} a_i^k(\phi(\mathbf{x}_i)\cdot\phi(\mathbf{x})) = \sum_{i=1}^{M} a_i^k K(\mathbf{x}_i, \mathbf{x}), \tag{3}$$

where z^k is its nonlinear principal component corresponding to ϕ. Since k=1,…,d, the d nonlinear principal components form a vector $\mathbf{z} = (z^1,\dots, z^d)^T$, which is the kernel eigen-emotion pattern (KEEP) for the multi-channel EEG recording during emotional processing. In this study, the Gaussian kernel $K(\mathbf{x},\mathbf{y}) = \exp(-\|\mathbf{x}-\mathbf{y}\|^2/2\sigma^2)$ is used as the kernel function, where σ is the kernel parameter. The number d of the chosen eigenvectors and σ can be optimized by means of cross validation.

G. Classification based on Adaptive SVM (ASVM)

Given a training set $\{z_i, y_i\}, i = 1,\dots, M$, where $z_i \in R^d$ are training data, and y_i are class label being either +1 or -1, let the weight vector and the bias of the separating hyperplane be $\mathbf{w}$ and b, the objective of SVM is to maximize the margin of separation and minimize the errors in the feature space, which is formulated as the constrained optimization problem:

$$\begin{aligned} &\textit{Minimize} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{M}\xi_i \\ &\textit{Subject to} \quad y_i\left(\mathbf{w}^T\phi(\mathbf{z}_i) + b\right) - 1 + \xi_i \geq 0, \quad \xi_i \geq 0, \quad \forall i \end{aligned} \tag{4}$$

where ξ_i are slack variables representing training errors, and C is the penalty weight. Since C is the same for both positive and negative classes, the learned separating hyperplane would be skewed toward to the smaller class, resulting in poor classification accuracy. The basic idea of adaptive SVM is to introduce different error costs C^+ and C^- for the positive and the negative class. If the size of positive class is larger, then set $C^+ < C^-$; otherwise $C^+ > C^-$. The adaptive SVM can be formulated as

$$\begin{aligned} &\textit{Minimize} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C^+\sum_{i\in I_+}\xi_i + C^-\sum_{i\in I_-}\xi_i \\ &\textit{subject to} \quad y_i\left(\mathbf{w}^T\phi(\mathbf{x}_i) + b\right) - 1 + \xi_i \geq 0, \xi_i \geq 0; \forall i \end{aligned} \tag{5}$$

where $I_+ = \{i \mid y_i = +1\}$ and $I_- = \{i \mid y_i = -1\}$. Introducing the Lagrangian method to (5) yields the dual problem as

$$\begin{aligned} &\textit{Maximize} \quad \sum_{i=1}^{M}\alpha_i - \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}\alpha_i\alpha_j y_i y_j K(\mathbf{z}_i, \mathbf{z}_j) \\ &s.t. \quad 0 \leq \alpha_i \leq C^+, \forall i \in I_+; 0 \leq \alpha_i \leq C^-, \forall i \in I_- \\ &\qquad \sum_{i=1}^{M}\alpha_i y_i = 0 \end{aligned} \tag{6}$$

where α_i are Lagrange multipliers. The training data for which $0 < \alpha_i \leq C^+$ or $0 < \alpha_i \leq C^-$ are support vectors (SVs). The class label for an unseen pattern $\mathbf{z}$ can be obtained by the decision function of adaptive SVM:

$$D(\mathbf{z}) = sign\left(\sum_{\mathbf{z}_i\in SV}\alpha_i y_i K(\mathbf{z}_i, \mathbf{z}) + b_o\right) \tag{7}$$

where b_o is the optimal bias, which can be determined by taking any training data whose $0 < \alpha_i < C^+$ or $0 < \alpha_i < C^-$ into the Kuhn-Tucker (KT) conditions. Finally, if $D(\mathbf{z}) > 0$, the data **z** belongs to positive class; negative class otherwise.

III. RESULTS

Here we compare the results of different combinations of feature extraction methods and classifiers. The best two-fold cross validation results of the combinations are listed in Table III and IV. Comparison between BP+NN with BP+PCA+NN show that the most widely-used PCA method in the BCI community did improve the accuracy of BP for both valence and arousal classifications, while the improvement is limited. In contrast, KEEP gives a significant improvement. Therefore, kernel PCA seems to be much more suitable than PCA in terms of feature extraction and dimensionality reduction for emotional EEG classification. The discrepancy can actually be explained by the different natures of the two methods. PCA is essentially a linear subspace method. However, EEG signal is non-stationary, and thus the EEG patterns are most likely nonlinearly distributed in the pattern space. Hence, performance of PCA would be limited due to its linear nature. On the contrary, since kernel PCA diagonalizes the data covariance in a nonlinear mapping induced feature space, the eigenvectors are nonlinearly related to the EEG patterns in the original space. Therefore, kernel PCA can better extract nonlinear characteristics of EEG patterns.

TABLE III. VALENCE CLASIFICATION RATES (IN %)

	P1	P2	P3	P4	P5	P6	P7	Ave
BP+NN	56	61	54	52	63.1	77	43	58.01
BP+PCA+NN	58	63	59	58	64.2	77	49	61.17
KEEP+NN	66	68	70	66.1	67	79	64	68.58
BP+SVM	72	74	64	59	75	77	56	68.14
KEEP+SVM	70	73	70	71	76	80	67	72.42
KEEP+ASVM	72	75	71	72	76	80	68	73.42

TABLE IV. AROUSAL CLASIFICATION RATES (IN %)

	P1	P2	P3	P4	P5	P6	P7	Ave
BP+NN	63	55	53	45.9	49	53	60	54.12
BP+PCA+NN	64	54	57	48	52	55	61	55.85
KEEP+NN	73	69	72	69	60	66.1	69	68.30
BP+SVM	73	69	71	67	57	63	68	66.85
KEEP+SVM	74	70	74	70	63	68	69	69.71
KEEP+ASVM	79	75	78	73	65	72	73	73.57

Furthermore, we can observe from Table III and IV that KEEP+ASVM performs better than KEEP+SVM, especially for the case of arousal classification where KEEP+ASVM outperforms KEEP+SVM by 3.86% (73.57-69.71). This can be understood by looking back at Table II: the data sets prepared for arousal classification are much more imbalanced than those prepared for valence classification. In summary, the highest classification rates for valence and arousal are 80% (participant 7) and 79% (participant 1), respectively, and are obtained by KEEP +ASVM. Also, KEEP+ASVM gives the best average classification accuracy for both valence (73.42%) and arousal (73.57%) classifications. To our best knowledge, the two results are the highest among the results reported in the current literatures in terms of single-trial EEG-based emotion recognition.

IV. CONCLUSION

In the current study, we have demonstrated that the combined use of KEEP and adaptive SVM show promising performance outcomes in emotional valence and arousal classifications. Nevertheless, future works are needed to further improve the current emotion recognition accuracy. For example, replacing the currently-used band power by other more robust spectral or spectral-temporal features (e.g., power spectral entropy and wavelet features) or proper channel selection may lead to better classification accuracy.

REFERENCES

[1] R. Davidson and N. Fox, "Asymmetrical brain activity discriminates between positive and negative stimuli infants," *Science,* vol. 218, no. 4578, pp. 1235–1237, 1982.

[2] R. Davidson, G. Schwartz, C. Saron, J. Bennett, and D. Goleman, "Frontal versus parietal eeg asymmetry during positive and negative affect," *Psychophysiology*, vol. 16, no. 2, pp. 202–203, 1979.

[3] R. W. Picard, E. Vyzas, and J. Healey, "Toward machine emotional intelligence analysis of affective physiological state," *IEEE Trans. Pattern Analysis and Machine Intel.*, vol. 23, pp. 1175-1191, 2001.

[4] R. Plutchik, *The Emotions: Facts, Theories, and a New Model*, New York: Random-House, 1962.

[5] P. Ekman. Basic emotions. In T. Dalgleish and M. Power, editors, Handbook of cognition and emotion, pages 45-60. Sussex, U.K.: John Wiley & Sons, Ltd., 1999.

[6] M. Li and B. L. Lu, "Emotion classification based on gamma-band EEG," in *Proc. 31st Annual Int. Conf. IEEE EMBS*, Minneapolis, Minnesota, USA, September 2-6, 2009, pp. 1323–1326.

[7] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from EEG using higher order crossings," *IEEE Trans. Information Technology in Biomedicine*, vol. 14, no. 6, pp. 186-197, 2010.

[8] A. Heraz, R. Razaki, and C. Frasson, "Using machine learning to predict learner emotional state from brainwaves." in *Proc. IEEE Int. Conf. Advanced Learning Technologies, 2007, pp.* 853-857.

[9] Y. P. Lin, J. H. Chen, J. R. Duann, C. T. Lin, and T. P. Jung, "Generalizations of the subject-independent feature set for music-induced emotion recognition," in *Proc. 33rd Annual Int. Conf. IEEE EMBS*, Boston, USA, Aug30 - Sept 3, 2011, pp. 6092-6095.

[10] M. Murugappan, M. Rizon, R. Nagarajan, and S. Yaacob, "Inferring of human emotional states using multichannel EEG," *European Journal of Scientific Research*, vol. 48, no. 2, pp.281-299, 2010.

[11] X. W. Wang, D. Nie, and B. L. Lu, "EEG-based emotion recognition using frequency domain features and support vector machines," *Lecture Notes in Computer Science*, vol. 7062, pp. 734–743, 2011.

[12] R. Horlings, D. Datcu, and L. M. R. Rothkrantz, "Emotion recognition using brain activity," in *Proc. 9th ACM Int. Conf. Computer Systems and Technologies*, Gabrovo, Bulgaria, 2008.

[13] R. Horlings, "*Emotion recognition using brain activity*," Master Thesis, Delft University of Technology, 2008.

[14] K. Schaaff and T. Schultz, "Towards an EEG-based emotion recognizer for humanoid robots." in Proc. *18th IEEE Int. Sym. Robot and Human Interactive Communication,* Roman, 2009, pp. 792-796.

[15] K. Schaaff and T. Schultz, "Towards emotion recognition from electroencephalographic signals," in Proc. *3rd Int. Conf. Affective Computing and Intelligent Interaction and Workshops*, 2009, pp. 1-6.

[16] D. Bamidis, C. Frantzidis, E. Konstantinidis, A. Luneski, C. Lithari, M. A. Klados, C. Bratsas, C. L. Papadelis, and C. Pappas, "*An integrated approach to emotion recognition for advanced emotional intelligence,*" *Lecture Notes in Computer Science*, vol. 5612, pp. 565-574, 2009.

[17] C. Frantzidis, C. Bratsas, C. Papadelis, and E. Konstantinidis, "Toward emotion aware computing: an Integrated approach using multichannel neurophysiological recordings and affective visual stimuli," *IEEE Trans. Information Tech. Biomedicine*, vol. 14, pp. 589–597, 2010.

[18] B. Schölkopf, A. Smola and K. R. Müller, "Nonlinear component analysis as a kernel eigenvalue problem," *Neural Computation,* vol. 10**,** pp.1299-1319, 1998.

[19] G. Wu and E.Y. Chang,"KBA: Kernel boundary alignment considering imbalanced data distribution," *IEEE Trans. Knowl. Data Eng.*, vol. 17, pp. 786–795, 2005.

[20] H. He and E.A. Garcia, "Learning from imbalanced data,". *IEEE Trans. Knowl. Data Eng.*, vol. 21, pp. 1263–1284, 2009.

[21] Y. H. Liu and Y. T. Chen, "Face recognition using total margin-based adaptive fuzzy support vector machines," *IEEE Trans. Neural Networks*, vol. 18, pp. 178-192, 2007.