Common Spatial Pattern Method for Channel Reduction in EEG-Based Emotion Recognition

Sepideh Hatamikia[1], Ali Motie Nasrabadi[2]

Received: 2015/10/9 Accepted: 2016/2/6

Abstract

Multi-channels Electroencephaloram (EEG) needs a long preparation time for electrode installation. Furthermore, using a large number of EEG channels may contain redundant and noisy signals which may deteriorate the performance of the system. Therefore, channels reduction is a necessary step to save preparation time, enhance the user convenience and retain high performance for an EEG-based system. In this study, we present a simple and practical EEG-based emotion recognition system by optimizing the channels number based on two different Common Spatial Pattern (CSP) channel reduction methods. We applied feature extraction based on the Fast Fourier Transform (FFT) algorithm and classification method based on the Support Vector Machine (SVM) and K-nearest neighbor (KNN) which make our proposed system an efficient and easy-to-setup emotion recognition system. According to experimental results, the proposed system using small number of channels not only does not increase the error of the system, but also improves the performance of the system compared to the use of total number of channels.

Keywords: Emotion recognition; Electroencephalogram (EEG); Channel reduction; Common Spatial Pattern (CSP)

1. Introduction

Emotions have a fundamental role in several aspects of our daily life, including learning, perception, attention, cognition, memory, behavior and decision making [1]. Furthermore, communication with social environment is entirely associated by the distinguishing of the mutual emotional states. Emotion recognition is a vital step towards designing advanced Brain Computer Interfaces (BCIs) in order to help people with neuromuscular disabilities [2]. Considering the importance of emotions in managing daily life of an individual, the need for designing brain computer interface (BCI) systems which can explore brain signals and detect user's emotional states for people with disabilities is growing. In such systems, revealing some of emotions like fear and stress can play a vital role for these patients in dangerous situations. Besides, in a practical BCI system, a limited number of channels are preferred. This reduction of number of EEG electrodes reduces computational complexity and calculation time and makes it more comfortable to be used by the subjects. Another important thing which is worth mentioning is that distinguishing of different emotional states can be used as a powerful tool to detect mental diseases and then, some neurotherapy training protocol can be provided for treatment approaches. There are different categorizations regarding to emotions in the literature, which the most common are discrete model proposed by Ekman et al. and continues model proposed by Russell [3,4]. In the discrete model, six distinct emotional states, acceptable for all cultures, proposed including: fear, anger, disgust, surprise, happiness and sadness. There are some classification regarding continuous model including two-dimensional, three-dimensional. In the two dimensional model, a continuous model is defined that consists of two continuous axis: valence and arousal. The valence axis varies from pleasant to unpleasant, while the arousal axis varies from exciting to quiet [5]. In this model, all the emotional states are scattered in a two dimensional space according to their level of valence and arousal [5]. In three-dimensional continuous model we have dominance dimension in addition to valence and arousal dimensions. The dynamic of the emotional states could be investigated by the physiological parameters from biological signals such as respiration rate, skin conductance, heart rate, Electrocardiogram (ECG), Electromyogram (EMG) and Electroencephalogram (EEG). Recently, emotion recognition based on EEG signals has achieved more attention by the researchers. To obtain high performance, most EEG-based recognition systems need signals from multiple channels on the scalp. However, using a large number of EEG channels may contain redundant and noisy signals which may deteriorate the performance of the system. Furthermore, signal recording based on the multi-channels EEG requires a long preparation time for electrodes placement that leads to inconvenience for the user.

1. M.Sc. Student, Department of Biomedical Engineering, Shahed University, Tehran, Iran. sepidehhatamikia@yahoo.com
2. Associate Professor, Department of Biomedical Engineering, Shahed University, Tehran, Iran. nasrabadi@shahed.ac.ir

Therefore, optimization of the number of channels is one of the most challenging issues in designing EEG-based systems. Common Spatial Pattern (CSP) is a very effective approach to derive spatial filters in the multi-channels EEG-based systems [6]. This algorithm is widely used for the analysis of motor imagery based BCIs. It is also used in another EEG recognition issues such as epileptic detection [7], source localization [8] and emotion recognition [9]. The results of previous studies have shown that CSP method have an ability to distinguish the emotional states [9-11]. Many previous studies proposed channel reduction and channel selection methods based on the CSP algorithm without decreasing the performance of the system. Farquhar et al. suggested a regularized CSP based method for channel selection in BCIs. They added l_1 norm regularization parameter to the basic optimization problem and proposed sparser CSP using conjugate gradient method [12].Some other studies also used sparse solutions in the CSP algorithm [13-14]. In these studies, by using sparse spatial filters, the signals are projected in the most discrimination direction using the least number of channels. Lv and Liu suggested a new BCI method based on the CSP and Binary Particle Swarm Optimization (BPSO) to find the optimal group of channels. They achieved high accuracy using a small number of channels [15]. Li and Koike proposed a new method to reduce the number of channels which used the classification performance of the CSP method as a function of the number of channels [16]. They showed that it is feasible to design an efficient BCI based on the CSP method with only five channels. In another method, a new approach in order to select optimal combination of channels in motor imagery BCIs was proposed which contribution scores of each channel was computed based on the CSP method [17]. In this method, all EEG channels were ordered by the contribution scores and the optimal subset of channels was chosen by comparing the classification accuracy ranks of all combinations. Wang et al. proposed a channel reduction method based on the CSP method for motor-imagery based BCIs. They selected the optimal channels by searching the maximums of the spatial patterns in the scalp mappings [18]. They achieved a high classification accuracy about 90% with four optimal channels.

In this study, we try to find the least number of channels for the EEG-based emotion recognition systems. As matter of fact, there are several studies which introduced different methods in order to channel reduction in EEG-based emotion recognition systems. As an example, Rizon et al. [19] suggested an asymmetric ratio (AR) based channel reduction method for human emotion recognition from EEG signals. In this research, features were extracted from the wavelet domain. Their experimental results showed that their method reduced the 28 pairs of channels to 2. For evaluating their method, they employed a fuzzy C-Means clustering algorithm to classify the emotions. They achieved minimum values of FPI (Fuzziness Partition Index) = 0.150051 and PME (Partition Modified Entropy) = 0.154724, and SD (standard deviation) = 0.328312 with 4 channels. As another example in [20] a method to classify two emotions based on EEG signals, which were positive and negative emotions elicited by pictures was proposed. The authors used the power spectrum from five bands and SVM as a classifier in a wrapper channel selection evaluation approach. In their experiment, they used a manual approach for reducing the number of channels. In [21], the authors used 14 channels for recording 4-s epochs. They achieved an 85.41% accuracy rate with seven pairs (14 channels: full) and 84.18% accuracy rate with five pairs, respectively. They reduced number of pairs of channels from 7 to 5 with almost the same accuracy in order to save computation time. The authors also found that frontal pairs of channels and high-frequency bands gave higher accuracy than other pairs of channels and lower frequency bands. In research [22], the authors proposed a novel deep belief network (DBN) method for examining critical channels. In fact, they explored critical channels by examining the weight distribution learned by DBN, The experiment results showed that DBN achieved the best average accuracy of 86.08% with the original whole 62 channels. They found optimal 4, 6, 9 and 12 channels, which achieve recognition accuracies of 82.88%, 85.03%, 84.02%, 86.65%, respectively, using SVM classifier. To the best of our knowledge, there is no study with the aim of CSP-based channel selection for emotion recognition systems. That's why we tried to investigate the ability of this method in such emotion EEG-based systems. For this aim, we used two different channel selection algorithm based on CSP algorithm. Our experimental results showed that the proposed system can find the optimal combination of channels for the EEG-based emotion recognition systems efficiently, and can balance both requirements for convenience and performance of the system. The organization and structure of this study is summarized as follows: Methods section consists of the research methodology by explaining data acquirement, description of CSP method and channel selection based CSP method. In the next section, the experimental results are presented and then conclusion of this study is represented in discussion and conclusion.

2. Methods

2.1. Data description

In our study, we used the MAHNOB HCI [23] dataset which includes EEG, gaze, audio, video and peripheral signals of 30 participants. 20 video clips, between 34.9s to117s long, were represented for each subject in order to extract 6 different emotions (joy, sad, fear, amusement, neutral and disgust). Furthermore, some emotionless clips as neutral stimuli were represented to the participants. After watching stimuli videos, participants were asked to use Self-Assessment Manikins (SAM) questionnaires to rate their felt emotions for valence and arousal dimensions [24]. 32 EEG channels from different positions, according to the Figure 1, were placed according to the 10-20 standard system. The sampling frequency was set at 256 Hz and the signals were recorded using BioSemi ActiveTwo system. We filtered the EEG signals (using FIR band-pass filter) between 8-13 Hz and 30-45 Hz to extract alpha and gamma sub-bands, respectively.

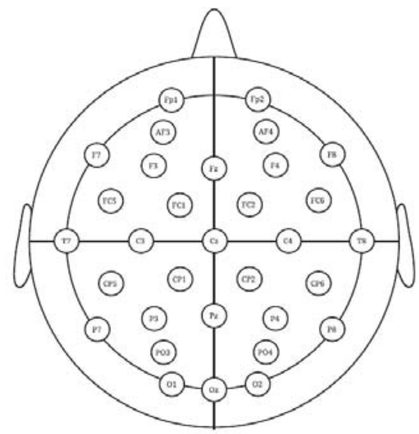

Figure 1. Electrode placement according 10-20 standard system

2.2. Common Spatial Pattern

The main aim of Common Spatial Pattern (CSP) is to construct a projection matrix to project the multi-channel EEG signals into low dimensional subspace using a linear transform [6]. In a two class problem, this algorithm tries to find spatial filters which leads to new time series; where the variance of one class is maximized while the variance of another class is minimized in the projected EEG time series. Assume X_1 and X_2 are EEG matrices under two classes with the size of $N\times T$, where N is the number of channels and T is the number of sample points for each channel [6, 18]. Normalized covariance matrices of EEG signals for each class can be computed as follow:

$$R_1 = \frac{X_1 X_1^T}{trace(X_1 X_1^T)},\quad R_2 = \frac{X_2 X_2^T}{trace(X_2 X_2^T)} \qquad (1)$$

where, X^T represents the transpose of X and trace(X) represents the sum of the diagonal elements of X. Then, all the trials of each class are averaged to compute averaged normalized covariance matrices $\overline{R}_1$ and $\overline{R}_2$. Composite covariance matrix R can be factorized as follow:

$$R = \overline{R}_1 + \overline{R}_2 = U_0 \Sigma U_0^T \qquad (2)$$

where U_0 and $\sum$ are the matrixes of eigenvectors and eigenvalues, respectively. Afterward, using the whitening transformation matrix:

$$P = \Sigma^{-\frac{1}{2}} U_0^T \qquad (3)$$

The average covariance matrices are transformed as:

$$S_1 = P\overline{R}_1 P^T,\ S_2 = P\overline{R}_2 P^T \qquad (4)$$

and if $S_1 = U\sum_1 U^T$ and $S_2 = U\sum_2 U^T$, then:

$$\Sigma_1 + \Sigma_2 = I. \qquad (5)$$

where, I is the identity matrix. As a result, the eigenvectors with the greater eigenvalues for S_F have the smallest value for S_H and contrariwise [6, 18].

With the projection matrix W:

$$W = U^T P. \qquad (6)$$

The EEG data is transformed as follow:

$$Z = WX. \qquad (7)$$

And EEG signals can be reconstructed as follow:

$$X = W^{-1} Z \qquad (8)$$

Where the matrix W^{-1} represents the inverse matrix of W which spatial patterns are considered the columns of W^{-1}. The first and last columns of W^{-1} have the most discriminative information that show the largest variance for one class and the smallest variance for another class [25].

2.3. Channel selection based on CSP algorithm

2.3.1. Method I

In the first method [18], optimal channels are selected by searching the maximums of the spatial patterns in the scalp mappings. Assume the spatial patterns of class 1 and class 2 are denoted as SP_1 and SP_2. With this method, the most optimal channels can be found by searching the maximum of the absolute value of SP_1 and SP_2 as follow [18]:

$$CH_1 = find(|SP_1| == Max(|SP_1|)) \quad (9)$$

$$CH_2 = find(|SP_2| == Max(|SP_2|)) \quad (10)$$

where, find () searches for the indices of the elements.

2.3.2. Method II

We employed the second channel reduction method according to the proposed method in [16, 17], in which a new approach for selecting optimal combination of channels is proposed which contribution score of each channel is computed based on the CSP method. In this method, all EEG channels should be ordered by the contribution scores and the optimal subset of channels is chosen by comparing the classification accuracy ranks of all combinations. Assume the first m column and last m columns of the spatial pattern matrix W^{-1} are considered as spatial pattern matrix of class 1 (D_1) and spatial pattern matrix of class 1 ($D2$). In order to rank the channels, the contribution score of the *i*-channel $D^i_{1\_score}$ and $D^i_{2\_score}$ can be computed as follow [16]:

$$D^i_{1\_score} = \|d_{1\_i}\|_1 / \|D_1\|_1 \quad (11)$$

$$D^i_{2\_score} = \|d_{2\_i}\|_1 / \|D_2\|_1 \quad (12)$$

where i represents the number of the channels, i ϵ (1, 2, 3,…,32), $\|X\|_1$ represents the l_1 norm of X, $d_{1\text{-}score}$ and $d_{2\text{-}score}$ represent the *i-st* row of D_1 and D_2. In this method, the channels are sorted according to the value of the $D^i_{1\text{-}score}$ and $D^i_{2\text{-}score}$ in descending order and the channels with greater values of the contribution score can provide the discriminative information better [17].Finally, the channels with larger values of $D^i_{1\text{-}score}$ and $D^i_{2\text{-}score}$ are used for the feature extraction and classification process. More information can be found in [16, 17].

3. Experimental results

In this study, 32-channels EEG data from 30 participants during audio-visual emotional stimulations were used. Our aim was to reduce the number of channels in order to provide an efficient emotion recognition system with optimal number of channels which could balance both requirements for convenience and performance of the system. For this aim, we examined two feature selection methods based on the CSP algorithm. Using these two channel selection algorithms, the optimal channels were selected according to the m first and last spatial filtered obtained in Eq. 8 , where m was considered as *(m=1, 2, 3, 4)*. After selecting the optimal channels, Fast Fourier Transform (FFT) algorithm was used as the feature extraction method to extract Power Spectrum Features (PSD) from alpha and gamma sub-bands which are informative bands for emotion analysis. PSD from these two different sub-bands were computed using fast Fourier transform (FFT) based on splitting the signal into overlapping 2-second segments and then PSD is estimated by averaging the segments. Next, the logarithms of the PSD from alpha sub-band (8 Hz < f < 10 Hz) and gamma sub-band (30 Hz < f < 45 HZ) were extracted from all 32 electrodes as features. So, for each pair of emotion, we have 60(=30 participants*2) ×64(32chanels*2sub-bands) matrices as the inputs of classifiers. The gamma sub-band was introduced as an optimal band for CSP-based emotion recognition [10]. Finally, the extracted features from the optimal channels were applied as the input of KNN and SVM classifier to classify different emotional states. The performance of the proposed method was evaluated by leave-one-out strategy as the cross validation method. In fact, in the training phase, the training dataset is divided into train and validation data in order to validate the accuracy estimation of our proposed system. For the SVM classifier, we employed linear kernel function and parameters of SVM classifier and the number of neighbors (K) for KNN classifier were selected based on the best obtained values using leave one out cross validation on the training set. Something which is worth mentioning is that, the frontal and temporal lobes are mainly related to emotion sensory activities reported in the previous literature on neurophysiological emotional response [26, 27]. That's why, we decided to compare the results of our proposed method with the case that some frontal electrodes are used for emotion detection. Classification results using original whole 32 EEG channels and also for a set of frontal electrodes FP1, FP2, F7, F8, F4, F3, T7 and T8 (related to the frontal, pre frontal and temporal area) without any channel reduction are shown in Table I and Table II.

Furthermore, the results of two mentioned channel reduction methods with the number of selected channels are represented in Table III and Table IV. For each pair of emotional class, the highest accuracies for method 1 and method 2 are shown in bold. These results illustrate that two proposed methods based on the CSP channel reduction and FFT feature extraction are efficient methods that can reduce the number of channels efficiently. According to the results, using less than 25% of total number of channels, the results are better compared to the results based on total number of channels. These results show that the proposed methods using small number of channels not only did not increase the error of the system, but also improve the performance of the system in many cases. The best selected channels for each pair of emotion separately, with their obtained accuracies are shown in Table V and Table VI. Furthermore, the most frequent electrodes for all pairs of emotions according to their number of repetition in different emotion pairs are shown with the line below them in Table V and Table VI. According to our results, these electrodes for alpha sub-band are PZ, P8, P3, CP2, PO4, PO3, F7 and FC2. Besides, the most frequent electrodes for gamma sub-band are PZ, CZ, FC1, FC2, F4, FZ, P3 and PO4. It is observed that different channels of different brain regions are selected by proposed channel reduction technique for different emotional classes. Comparing the results of Table I and II with the result of Table V and Table VI shows that higher classification accuracies are achieved using our proposed channel reduction method compared to frontal electrodes for classification of all pairs of emotional classes. Comparing the results of Table V and Table VI shows that higher classification accuracies are achieved using gamma sub-band for both methods and for all pairs of emotional classes.

4. Discussion and Conclusion

In this research, we have shown that it is feasible to design a simple but effective EEG-based emotion recognition system using CSP-based channel reduction. According to the results, the proposed system can save computational time and retain high performance using small number of channels (maximum of 8 channels). In the literature, CSP method has introduced as an efficient subject-dependent channel reduction method for motor imagery based BCIs which can reduce the number of channels without increasing the system error [12-18]. In this study, the suggested emotion recognition system based on CSP method has the advantage of subject-independence and user comfort. We have demonstrated that the proposed system is an efficient system that can find the least number of channels for subject independent EEG-based emotion recognition systems efficiently and can balance both requirements for convenience and performance of the system. Furthermore, according to the experimental results above, the optimal selected channels can also improve the performance of the emotion recognition system compere to the use of the total number of channels. Compared to previously published works which proposed efficient channel reduction methods, we achieved more efficient system; since, in spite of the fact that the number of electrodes has decreased to less than 25% of total number of channels, the performance of system has increased in many cases which shows the efficiency of our suggested system. While, previous channel reduction methods based on EEG signals [20-22] were at most able to reduce the number of channels with the same accuracy. However, the lack of equal database and some items such as data acquisition, number of participates and the type of stimuli affect the classification accuracy. Furthermore, in some cases, the difference in the number of emotional states does not provide the same conditions for comparison of the accuracy of the published works. Davidson et al. [26] proposed that frontal electrical activity was associated with the negative and positive emotions and induction of emotional states mainly activate frontal circuits compared to other regions in the brain. Also, Harmon, & Ray [27] found that positive and negative emotional states may produce distinct patterns of frontal, parietal and temporal EEG activity. These results show that the frontal and temporal lobes are mainly related to emotion sensory activities. That’s why, we decided to compare the results of our proposed method with the case that some frontal electrodes are used for emotion detection. Our results show that optimizing combination of electrodes with our channel reduction method has improved the results in comparison with frontal electrodes which are introduced as the most related electrodes with emotional states. Our results show that the selected channels for both each pair of emotion and all emotions, are not limited to the frontal lobe, but they are related to different area of brain which these results are consistent to the results of previous studies [28-33]. Due to the fact that our aim is optimizing the number of channels, and in the case of all pairs of emotional states we were able to reduce the number of the channels effectively, we have to acknowledge that we achieve our aim regarding channel reduction problem, and investigation for more accurate features in determining emotional states based on EEG signals will be done in the future study. In summarized, the strength points of our study are originated from two reasons. The first positive point which must be mentioned is employing CSP-based methods in order to select and reducing the number of channels in an emotion recognition system for the first time in literature, and showing the ability of these CSP-based channel reduction methods in such a problem. Another positive point about our proposed system which is really worth mentioning is that suggested system is an effective system which is very easy to implement. In comparison to previous studies, something which makes our proposed system special is that it can be easily implemented, and at the same time it has an effective performance and is considered as an efficient channel reduction emotion EEG-based system. To be more precise, we applied feature extraction based on the FFT algorithm and classification method based the SVM and KNN. As matter of fact, in addition to CSP method, using such simple feature extraction and classification methods makes our proposed channel reduction procedure efficient for on-line applications with an easy computation. Furthermore, our proposed system may help to develop a practical EEG-based emotion recognition system. However, the noise and artifacts would badly effect on the constructed CSP spatial filters. In the future, we will focus on Local Temporal Common Spatial Patterns (LTCSP) method which is introduced as the robust CSP based method under outlier condition to reduce the effect of noise on the designed system [34]. It has been shown that biological systems like brain are intrinsically complex, non-stationary and nonlinear [35]. Nonlinear analysis methods make it possible to obtain more informative characteristics of complex dynamic of the brain activity. Therefore, our future works is going to include modifications to the suggested emotion recognition system to be more accurate by examining nonlinear features and also to extend our approach in the arousal–valence emotional space.

References

[1] R. Picard, E. vyzas, J. Healy, “ Toward machine emotional intelligence: Analysis of affective physiological state”, IEEE Trans Pattern Anal Mach Intell, 23, 2001, 1175-1191.

[2] S.Hatamikia, A.M Nasrabadi, N.Shourie, “Plausibility Assessment of a Subject Independent Mental Task-Based BCI Using Electroencephalogram Signals,” 21st Iranian Conference on Biomedical Engineering (ICBME 2014), Biomedical Engineering Faculty, Amirkabir University ofTechnology (Tehran Polytechnic), Tehran, Iran,Nov 26-28, 2014.

[3] P. Ekman, WV. Friesen, M. O’Sullivan, A. Chan, et al., “Universals and cultural differences in the judgments of facial expressions of emotion”, J Pers Soc Psychol, 53, 1987, 712-717.

[4] JA. Russell, “A circumplex model of affect”. J Pers Soc Psychol, 39, 1980, 1161‐1178.

[5] S. Hatamikia, K. Maghooli, AM. Nasrabadi, “The emotion recognition system based on autoregressive model and sequential forward feature selection of electroencephalogram signals”, J Med Sign Sence, 4, 2014, 194-201.

[6] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, “Optimal spatial filtering of single trial EEG during imagined handmovement”, IEEE Trans Rehabil Eng, 8, 2000, 441–446.

[7] P. Xu, X. Xiong, Q Xue, P Li, “Differentiating Between Psychogenic Nonepileptic Seizures and Epilepsy Based on Common Spatial Pattern of Weighted EEG Resting Networks”, IEEE Trans Biomed Eng, 61, 2014, 1747 - 1755.

[8] ZJ. Koles, AC. Soong, “EEG source localization: implementing the spatio-temporal decomposition approach”, Electroencephalogr Clin Neurophysiol, 107, 1998, 343-352.

[9] M. Molavi, Jb. Yunus, E. Akbari, “Comparison of Different Methods for Emotion Classification”, Proceeding. AMS '12 Proceedings of the *2012 Sixth Asia Modelling Symposium*, Bali, May 2012, 50-53.

[10] M. Li, BL. Lu, “Emotion Classification Based on Gamma-band EEG”, 31st Annual International Conference of the IEEE EMBS, Minneapolis, Minnesota, USA, 2009, 1323-1326.

[11] S. Makeig, G. Leslie, T. Mullen,Devpratim Sarma,Nima Bigdely-Shamlo, and Christian Kothe, “First Demonstration of a Musical Emotion BCI ”, springer, LNCS 6975, 2011, 487–496.

[12] J. Farquhar, N. Hill, T. Lal, B. Sch¨olkopf, “Regularised CSP for sensor selection in BCI,” in Proceedings of the 3rd International Brain-Computer Interface Workshop and Training Course, 2006, 14-15.

[13] X. Yong, R. K. Ward, G. E. Birch, “Sparse spatial filter optimization for EEG channel reduction in brain-computer interface,” in Proc. IEEE Int. Conf. Acoustics, Speech Signal Process,USA , 2008, 417–420.

[14] M. Arvaneh, C. Guan, K. K. Ang, C. Quek, “Optimizing the Channel Selection and

Classification Accuracy in EEG-Based BCI", IEEE Trans Biomed Eng, 58, 2011, 1865–1873.

[15] J. Lv, M. Liu, "Common Spatial Pattern and Particle Swarm Optimization for Channel Selection in BCI," in 3rd International Conference on Innovative Computing Information and Control, 2008, 457–460.

[16] Y. Li, Y. Koike, "A real-time BCI with a small number of channels based on CSP", Neural Comput Applic, 20, 2011, 1187–1192.

[17] M. Li, J. Ma, S. Jia, "Optimal Combination of Channels Selection Based on Common Spatial Pattern Algorithm", Proceedings of the 2011 IEEE International Conference on Mechatronics and Automation, Beijing, China, 2011, 7 – 10.

[18] Y. Wang, Sh. Gao, X. Gao, "Common Spatial Pattern Method for Channel Selelction in Motor Imagery Based Brain-computer Interface", 27th Annual International Conference of the IEEE-EMBS, Shanghai, China, 2005.

[19] M Rizon, M. Murugappan, R. Nagarajan, S. Yaacob, "Asymmetric ratio and FCM based salient channel selection for human emotion detection using EEG". WSEAS Trans. Signal Process. 4, 2008.

[20] N. Jatupaiboon, S. Pan-ngum, P. Israsena, "Emotion classification using minimal EEG channels and frequency bands". Proceedings of 10th Int'l Joint conf. on Computer Science and Software Engineering (JCSSE 2013, Khon Kaen, Thailand.

[21] T. Alotaiby, F. E Abd El-Samie, S.A Alshebeili, I. Ahmadm et al. "A review of channel selection algorithms for EEG signal processing" EURASIP Journal on Advances in Signal Processing , 66, 2015, 1-21.

[22] W.L Zheng, H. T Guo and B. L. Lu, *"*Revealing Critical Channels and Frequency Bands for Emotion. Recognition from EEG with Deep Belief Network*",* IEEE EMBS Conference on Neural Engineering, France, 2015, 22-24.

[23] M. Soleymani, J. Lichtenauer, T. Pun, M. Pantic, "A multi-modal affective database for affect recognition and implicit tagging", IEEE Trans Affect Comput, 3, 2012, 42–55.

[24] S. Hatamikia, A.M Nasrabadi, "Recognition of Emotional States Induced by Music Videos Based on Nonlinear Feature Extraction and SOM Classification", 21th Iranian conference ICBME, Iran, Tehran, November 2014, 333-337.

[25] S.Hatamikia, A.M Nasrabadi, "Subject transfer BCI based on Composite Local Temporal Correlation Common Spatial Pattern", Comput Biol Med, 64, 2015, 1-11.

[26] Davidson, R.J., Schwartz, G.E., Saron, C., Bennett, J. & Goleman, D.J. "Frontal versus parietal EEG asymmetry during positive and negative affect". Psychophysiology, 16, 1979, 202-203.

[27] Harman, D. W., & Ray, W. J. (1977). "Hemispheric activity during affective verbal stimuli: An EEG study". Neuropsychologia, 15, 1977, 457-460.

[28]. S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, I. Patras, "DEAP: a database for emotion analysis using physiological signals", IEEE Trans. Affect. Comput, 3, 2012, 18–31.

[29]. Sander Koelstra , Ioannis Patras, "Fusion of facial expressions and EEG for implicit affective tagging", Image and Vision Computing, 31, 2013, 164-174.

[30] Robert Jenke, Angelika Peer, Member and Martin Buss, "Feature Extraction and Selection for Emotion Recognition from EEG", IEEE TRANSACTIONS ON AFFECTIVE COMPUTING, 5, 2014, 327-339.

[31]. Wei-Long Zheng, Hao-Tian Guo and Bao-Liang Lu, "Revealing Critical Channels and Frequency Bands for Emotion Recognition from EEG with Deep Belief Network", 7th Annual International IEEE EMBS Conference on Neural Engineering Montpellier, France, 22 - 24 April, 2015

[32]. Murugappan Murugappan, Nagarajan Ramachandran, Yaacob Sazali, "Classification of human emotion from EEG using discrete wavelet transform, J. Biomedical Science and Engineering", 3, 2010, 390-396.

[33]. Henry Candra, Mitchell Yuwono, Ardi Handojoseno, Rifai Chai, Steven Su, and Hung T. Nguyen, "Recognizing emotions from EEG subbands using wavelet analysis", 2015 37th Annual International Conference of the IEEE, Engineering in Medicine and Biology Society (EMBC), Milan, 25-29, Aug. 2015 6030 – 6033.

[34]. S.Hatamikia, A.M Nasrabadi , "Subject Independent BCI Based on LTCCSP Method and GA Wrapper Optimization", Iranian Research Organization for Science and Technology (IROST), Tehran, Iran, 25-27 November 2015, 797-802.

[35]. S. Hatamikia, A.M Nasrabadi, N. Shourie, "Analysis of Inter-hemispheric and Intra-hemispheric Differences of the Correlation Dimension in the Emotional States Based on EEG Signals 22nd Iranian Conference on Biomedical Engineering(ICBME 2015) ", Iranian Research Organization for Science and Technology (IROST), Tehran, Iran, 25-27 November 2015, 6-9.

Table 1. Classification accuracies (%) usng all channels based on the gamma subband

Emotional classes	Channels	SVM Classifier	KNN classifier	Emotional classes	Number Of channels	SVM Classifier	KNN classifier
Joy-Neutral	All 32 channels	94.64	91.07	**Fear-Joy**	All 32 channels	78.57	60.26
Joy-Neutral	Frontal set	73.21	66.67	**Fear-Joy**	Frontal set	62.50	48.15
Sad-Neutral	All 32 channels	85.71	89.29	**Fear-Disgust**	All 32 channels	67.86	55.56
Sad-Neutral	Frontal set	66.07	66.67	**Fear-Disgust**	Frontal set	44.64	53.70
Joy-Sad	All 32 channels	53.57	51.79	**Fear-Neutral**	All 32 channels	78.57	81.48
Joy-sad	Frontal set	51.79	51.85	**Fear-Neutral**	Frontal set	75.00	62.96
Disgust-sad	All 32 channels	47.36	46.52	**Sad-Fear**	All 32 channels	76.00	69.52
Disgust-sad	Frontal set	50.43	47.80	**Sad-Fear**	Frontal set	57.14	50.00
Amusement -Fear	All 32 channels	71.43	60.26	**Disgust-Neutral**	All 32 channels	89.29	84.04
Amusement -Fear	Frontal set	58.93	51.85	**Disgust-Neutral**	Frontal set	76.79	72.22
Amusement -Neutral	All 32 channels	89.29	87.04	**Disgust-Joy**	All 32 channels	51.07	51.07
Amusement -Neutral	Frontal set	69.64	64.81	**Disgust-Joy**	Frontal set	54.21	50.12
Amusement -Sad	All 32 channels	48.29	45.20	**Digust-Amusement**	All 32 channels	53.50	55.85
Amusement -Sad	Frontal set	55.36	41.20	**Digust-Amusement**	Frontal set	51.16	53.48

Table 2. Classification accuracies (%) usng all channels based on the alpha subband

Emotional classes	Number Of channels	SVM Classifier	KNN classifier	Emotional classes	Number Of channels	SVM Classifier	KNN classifier
Joy-Neutral	All 32 channels	92.86	87.50	**Fear-Joy**	All 32 channels	67.86	64.81
Joy-Neutral	Frontal set	82.14	83.33	**Fear-Joy**	Frontal set	66.07	55.56
Sad-Neutral	All 32 channels	93.75	75.00	**Fear-Disgust**	All 32 channels	66.07	58.15
Sad-Neutral	Frontal set	78.57	83.33	**Fear-Disgust**	Frontal set	60.71	51.85
Joy-Sad	All 32 channels	49.50	55.36	**Fear-Neutral**	All 32 channels	80.36	75.93
Joy-Sad	Frontal set	44.64	44.44	**Fear-Neutral**	Frontal set	75.00	75.93
Disgust-sad	All 32 channels	46.43	45.18	**Sad-Fear**	All 32 channels	62.50	57.41
Disgust-sad	Frontal set	53.79	41.48	**Sad-Fear**	Frontal set	66.07	53.70
Amusement -fear	All 32 channels	67.78	61.11	**Disgust-Neutral**	All 32 channels	83.93	83.33
Amusement -fear	Frontal set	66.07	51.85	**Disgust-Neutral**	Frontal set	80.36	85.15
Amusement -Neutral	All 32 channels	85.71	87.04	**Disgust-Joy**	All 32 channels	45.21	44.87
Amusement -Neutral	Frontal set	78.57	77.78	**Disgust-Joy**	Frontal set	42.86	48.89
Amusement -Sad	All 32 channels	54.21	50.10	**Digust-Amuseme nt**	All 32 channels	54.01	57.85
Amusement -Sad	Frontal set	41.07	45.93	**Digust-Amuseme nt**	Frontal set	53.57	57.41

Table 3. Classification accuracies (%) based on the CSP channel reduction using gamma subband

Emotional classes	Method	Number Of channels	SVM Classifier	KNN classifier	Emotional classes	Method	Number Of channels	SVM Classifier	KNN classifier
Joy-Neutral	1	2	73.21	69.64	**Fear-Joy**	1	2	83.93	83.33
	2	2	83.93	75.00		2	2	78.57	70.37
	1	4	85.71	89.29		1	4*	85.71	**89.04**
	2	4	85.71	75.00		2	4	80.36	75.93
	1	6*	89.29	**96.43**		1	6	85.71	85.19
	2	6	89.29	83.93		2	6	80.36	79.63
	1	8	92.86	94.64		1	8	85.71	84.64
	2	8*	**96.43**	87.50		2	8*	**83.36**	77.93
Sad-Neutral	1	2	73.21	78.57	**Fear-Disgust**	1	2*	70.64	**67.81**
	2	2*	92.86	**94.64**		2	2*	**75.21**	67.81
	1	4	83.93	87.50		1	4	66.50	58.85
	2	4	91.07	92.86		2	4	75.21	60.12
	1	6	85.71	85.71		1	6	66.50	56.70
	2	6	91.07	91.07		2	6	75.21	58.20
	1	8*	**96.43**	83.96		1	8	67.86	55.56
	2	8	94.64	92.86		2	8	66.07	56.70
Joy-Sad	1	2	57.14	47.50	**Fear-Neutral**	1	2	56.43	72.22
	2	2	57.14	51.79		2	2	71.43	64.81
	1	4*	**60.93**	52.61		1	4	76.79	72.22
	2	4	51.79	46.43		2	4*	73.21	**75.93**
	1	6	57.14	42.86		1	6	75.00	77.78
	2	6*	**60.93**	48.21		2	6	71.43	66.67
	1	8	60.93	51.79		1	8*	**80.36**	75.93
	2	8	51.79	48.21		2	8	75.00	66.67
Disgust-sad	1	2*	54.64	**64.11**	**Sad-Fear**	1	2	87.50	81.48
	2	2*	**61.93**	50.04		2	2*	85.71	**81.48**
	1	4	51.07	49.81		1	4*	**91.29**	86.19
	2	4	57.56	50.04		2	4	87.50	75.93
	1	6	52.86	51.07		1	6	85.71	85.39
	2	6	53.19	48.19		2	6	91.29	78.93
	1	8	46.71	48.04		1	8	85.71	85.39
	2	8	53.19	50.04		2	8	87.50	78.07
Amusement-fear	1	2	59.93	68.67	**Disgust-Neutral**	1	2	64.50	60.56
	2	2	62.50	60.41		2	2	62.50	62.96
	1	4	74.43	67.81		1	4*	**92.86**	77.78
	2	4	62.71	64.96		2	4*	87.50	**92.59**
	1	6	74.43	76.07		1	6	91.07	77.78
	2	6*	73.21	**70.67**		2	6	82.14	74.04
	1	8*	**78.30**	62.50		1	8	89.29	85.19
	2	8	69.76	64.81		2	8	85.71	81.48
Amusement-Neutral	1	2	82.14	70.37	**Disgust-Joy**	1	2*	**61.36**	53.70
	2	2*	83.93	**88.89**		2	2*	53.43	**56.43**
	1	4	83.93	87.74		1	4	58.79	50.20
	2	4	83.93	88.89		2	4	51.07	50.20
	1	6*	**85.71**	86.15		1	6	58.79	51.07
	2	6	85.71	81.48		2	6	50.20	48.60
	1	8	82.14	85.71		1	8	51.07	51.82
	2	8	85.71	88.89		2	8	51.07	51.07
Amusement-Sad	1	2*	**55.79**	50.80	**Digust-Amusement**	1	2*	59.57	**65.96**
	2	2*	51.43	**54.43**		2	2	58.00	53.44
	1	4	49.43	45.13		1	4	59.79	54.44
	2	4	45.29	44.89		2	4*	**61.57**	60.85
	1	6	50.86	42.01		1	6	57.82	65.09
	2	6	45.72	44.89		2	6	56.30	55.43
	1	8	49.43	53.04		1	8	54.64	60.85
	2	8	49.29	48.31		2	8	54.64	65.10

*.indicated the number of channels with the highest classification accuracy

Table 4. Classification accuracies (%) based on the CSP channel reduction using alpha subband

Emotional classes	Method	Number Of channels	SVM Classifier	KNN classifier	Emotional classes	Method	Number Of channels	SVM Classifier	KNN classifier
Joy-Neutral	1	2	67.86	64.29	**Fear-Joy**	1	2	55.00	62.21
	2	2	82.14	83.93		2	2	54.57	63.26
	1	4	64.29	60.71		1	4	57.58	66.20
	2	4	80.36	80.36		2	4	60.14	63.26
	1	6	78.57	75.00		1	6	62.21	62.21
	2	6	85.71	87.50		2	6	61.93	63.26
	1	8*	87.50	**89.29**		1	8*	**63.46**	63.94
	2	8*	89.29	**92.10**		2	8*	62.21	**66.37**
Sad-Neutral	1	2	82.14	85.71	**Fear-Disgust**	1	2	56.57	58.56
	2	2	82.14	82.14		2	2	60.14	61.11
	1	4*	85.71	**89.29**		1	4	61.93	56.57
	2	4	83.93	80.36		2	4	56.57	55.58
	1	6	89.29	85.71		1	6	64.71	56.10
	2	6	85.71	82.14		2	6*	61.93	**63.93**
	1	8*	**94.64**	89.29		1	8*	**70.07**	59.85
	2	8	85.10	78.57		2	8	61.93	59.85
Joy-Sad	1	2	48.50	46.43	**Fear-Neutral**	1	2	55.60	69.70
	2	2	42.50	55.36		2	2	71.86	66.96
	1	4	51.79	53.57		1	4	78.01	67.17
	2	4*	55.36	**58.14**		2	4	71.64	70.37
	1	6*	50.70	**58.14**		1	6	74.21	69.70
	2	6	55.36	51.79		2	6	73.21	70.37
	1	8	50.00	51.10		1	8*	74.21	**74.21**
	2	8	55.36	51.79		2	8*	**84.18**	78.01
Disgust-sad	1	2*	48.57	**54.59**	**Sad-Fear**	1	2	60.93	59.41
	2	2*	**54.10**	49.89		2	2	60.93	56.50
	1	4	47.50	42.60		1	4	64.50	70.52
	2	4	47.50	50.89		2	4	61.93	59.80
	1	6	46.93	43.70		1	6*	**73.64**	69.67
	2	6	42.14	51.50		2	6	61.93	70.52
	1	8	42.14	43.70		1	8	72.64	65.96
	2	8	48.57	50.89		2	8*	62.14	**73.37**
Amusement-fear	1	2*	59.36	**67.81**	**Disgust-Neutral**	1	2	66.07	68.52
	2	2	60.00	64.96		2	2	53.70	68.81
	1	4	61.14	59.36		1	4*	78.57	**85.19**
	2	4*	59.87	**73.37**		2	4	71.43	63.26
	1	6	62.14	58.85		1	6	82.14	81.48
	2	6	61.14	71.67		2	6	75.00	72.20
	1	8	62.14	57.60		1	8	82.14	79.63
	2	8	60.48	66.15		2	8*	**77.78**	75.00
Amusement-Neutral	1	2	71.43	75.93	**Disgust-Joy**	1	2*	**56.43**	54.70
	2	2	67.86	81.48		2	2	53.43	53.43
	1	4	71.43	70.36		1	4	51.79	49.20
	2	4	67.76	66.67		2	4	51.07	49.20
	1	6	83.93	79.64		1	6	48.79	51.07
	2	6	83.93	81.48		2	6	50.20	48.60
	1	8*	**85.71**	83.33		1	8	42.07	49.82
	2	8*	83.93	**83.93**		2	8*	42.07	**56.43**
Amusement-Sad	1	2*	48.79	**59.56**	**Digust-Amusement**	1	2	59.57	55.96
	2	2*	**51.43**	53.13		2	2	58.28	53.44
	1	4	49.43	45.13		1	4*	59.19	**65.44**
	2	4	45.29	44.89		2	4	59.07	50.85
	1	6	50.86	48.01		1	6	57.82	54.09
	2	6	45.72	50.89		2	6	56.30	51.23
	1	8	50.49	53.04		1	8	56.63	50.85
	2	8	50.49	52.31		2	8*	56.63	**59.10**

*.indicated the number of channels with the highest classification accuracy

Table5. the best selected channels with the obtained accuracies (%) using alpha subband

Emotionl classes	Method	Number Of channels	Classifier (accuracy)	Selected channels	Emotionl classes	Method	Number Of channels	Classifier (accuracy)	Selected channels
Joy-Neutral	1	8	KNN (89.29)	PZ, PO4, P8, PO3,C4, P3, FC5, FC2	**Fear-Joy**	1	8	SVM (63.46)	PZ, PO4, CP2, C4, F7,P8, T7, CP5
Joy-Neutral	2	8	KNN (92.10)	CP5, T8, CZ, PO4, O1,P3, OZ, FC2	**Fear-Joy**	2	8	KNN (66.37)	T8, PO3, O1, FC6, F4, P7, T7, FP2
Sad-Neutral	1	8	SVM (94.64)	PZ, FC5, P8, T8, PO4, CZ CP2, FZ	**Fear-Disgust**	1	8	SVM (70.07)	PZ, F7, FP1, FC2, P8, C4, FP2, CP2
Sad-Neutral	2	6	SVM (85.71)	CP2, CZ, O1, AF4, PO4, T8	**Fear-Disgust**	2	6	KNN (63.93)	F4, FP2, PZ, CP2, T8, CP5
Joy-Sad	1	6	KNN (58.14)	PZ, P8, PO4 FC5, PO3, T8	**Fear-Neutral**	1	8	KNN (74.21)	PZ, CP2, PO4, F7, P8, PO3, C4, P8
Joy-Sad	2	4	KNN (58.14)	O1, PO4, P8, P3	**Fear-Neutral**	2	8	SVM (84.18)	CP6, F7, P3, CP2, O1, PO4, FC1, FC2
Disgust-sad	1	2	KNN (54.59)	P3, Pz	**Sad-Fear**	1	6	SVM (73.64)	PZ, CP2, FC5, F7, P8, C4
Disgust-sad	2	2	SVM (54.10)	PO3, F7	**Sad-Fear**	2	8	SVM (73.37)	T8, F3, F7, P3, O2, FC6, PO3, FZ
Amusement-fear	1	2	KNN (67.81)	CP2, PO4	**Disgust-Neutral**	1	4	KNN (85.19)	PZ, FC2, P8, P3
Amusement-fear	2	4	KNN (73.37)	CP5, FZ, PO3, FC6	**Disgust-Neutral**	2	8	SVM (77.78)	PZ, P3, AF3, O1, PO3, FC2, PO4, CP2,
Amusement-Neutral	1	8	SVM (85.81)	P3,PO4, F4, T8, F7, CP2, FC2, PZ	**Disgust-Joy**	1	2	SVM (56.43)	FC6, PZ
Amusement-Neutral	2	8	KNN (83.93)	PO4, PZ, P3, F7, C3, P8, C4, FC2	**Disgust-Joy**	2	8	KNN (56.43)	CP5, P3, FC6, O1, PO3, CP2, FC5, CP6
Amusement-Sad	1	2	KNN (59.56)	P3, PO4	**Digust-Amusement**	1	2	KNN (65.44)	P3, PO3
Amusement-Sad	2	2	SVM (51.43)	PZ, P8	**Digust-Amusement**	2	4	KNN (59.10)	FP2, PO3, FC2, CP6

The most frequent electrodes are shown with the line bellow them

Table 6. the best selected channels with the obtained accuracies (%) using gamma subband

Emotionl classes	Method	Number Of channels	Classifier (accuracy)	Selected channels	Emotionl classes	Method	Number Of channels	Classifier (accuracy)	Selected channels
Joy-Neutral	1	6	KNN (96.43)	FC2, FZ, P4, T8, CZ, FC1	**Fear-Joy**	1	4	KNN (89.04)	PZ,FC1, PO4,P7
Joy-Neutral	2	8	SVM (96.43)	FC2, T8, P4, AF4, FZ, CZ, FC1, CP5	**Fear-Joy**	2	8	SVM (83.36)	PZ, P3, FZ, F4, F7, CZ, F3, O2
Sad-Neutral	1	8	SVM (96.43)	FZ, PO4, PZ, CP5, CZ, F8, AF4, P4	**Fear-Disgust**	1	2	KNN (67.81)	F7, CP2
Sad-Neutral	2	2	KNN (94.64)	PZ, FC1	**Fear-Disgust**	2	2	SVM (75.21)	CZ, P3
Joy-Sad	1	4	SVM (60.93)	T8, P3, C4, F4	**Fear-Neutral**	1	8	SVM (80.36)	CZ, FC1, PO3, P7, FC2, FZ, P3, F4
Joy-Sad	2	6	SVM (60.93)	PO4, C4, C3, P3, FC5, FC2,	**Fear-Neutral**	2	4	KNN (75.93)	P4, P7, PZ, PO4
Disgust-sad	1	2	KNN (64.11)	F4, F3	**Sad-Fear**	1	4	SVM (91.29)	PZ, FC1, FC2, P7
Disgust-sad	2	2	SVM (61.93)	PO3, CP6	**Sad-Fear**	2	2	KNN (81.48)	P3, FC1
Amusement-fear	1	8	SVM (78.30)	F7, PZ, F4, FC2, PO4, CP2, PO3, P3	**Disgust-Neutral**	1	4	SVM (92.86)	F4, PZ,P3, FC2
Amusement-fear	2	6	KNN (70.67)	PO3, PO4, C3, P3, FZ	**Disgust-Neutral**	2	4	SVM (92.59)	PZ, CP6, PO4, CZ
Amusement-Neutral	1	6	SVM (85.71)	F4, FC2, P3, FC1, CZ, FZ	**Disgust-Joy**	1	2	SVM (61.36)	FC2, CZ
Amusement-Neutral	2	2	KNN (88.89)	CZ, PO4	**Disgust-Joy**	2	2	KNN (56.43)	PZ, P3
Amusement-Sad	1	2	SVM (55.79)	F4, P8	**Digust-Amusement**	1	2	KNN (65.96)	P3, PO4
Amusement-Sad	2	2	KNN (54.43)	PZ, PO4	**Digust-Amusement**	2	4	SVM (61.57)	FP2, PO4, FC2, T8

The most frequent electrodes are shown with the line bellow them