Emotion Classification using Minimal EEG Channels and Frequency Bands

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***Abstract*—In this research we propose to use EEG signal to classify two emotions (i.e., positive and negative) elicited by pictures. With power spectrum features, the accuracy rate of SVM classifier is about 85.41%. Considering each pair of channels and different frequency bands, it shows that frontal pairs of channels give a better result than the other area and high frequency bands give a better result than low frequency bands. Furthermore, we can reduce number of pairs of channels from 7 to 5 with almost the same accuracy and can cut low frequency bands in order to save computation time. All of these are beneficial to the development of emotion classification system using minimal EEG channels in real-time.**

***Keywords*—electroencephalogram; emotion; human computer interaction; support vector machine**

I. INTRODUCTION

The aim of Human Computer Interaction (HCI) is to improve the interactions between human and computers. Because most computers lack of understanding user's emotions, sometimes they are unable to respond to the user's needs automatically and correctly. In the past decades, most of emotion classification researches have only focused on using facial expressions and speech. However, it's easy to fake facial expressions or change tone of speech and these signals are not continuously available. It differs from using physiological signals, which occur continuously and are hard to conceal, such as Galvanic Skin Response (GSR), Electrocardiogram (ECG), Skin Temperature (ST) and especially Electroencephalogram (EEG) the signal from voltage fluctuations in the brain that is the center of emotions [1], [4], [5], [6].

Nowadays the emotion classification research using EEG signal is highly interested. Ref. [2], [3] found relation between valence emotion and power spectrum asymmetry which can be computed from difference of power spectrum of pairs of channels that are symmetry (e.g., AF3-AF4 and F7-F8). The power spectrum is widely used to investigate emotion relation which can be found in following researches. Ref. [4] classified three emotions (i.e., exciting positive, exciting negative and calm neutral) elicited by recall. The accuracy rate was about 63%. Ref. [5] classified four emotions (i.e., joy, pleasure angry and sadness) elicited by picture. The accuracy rate was about 92.73%. Ref. [6] classified two emotions (i.e., positive and negative) elicited by movie clip. The accuracy rate was about 87.53%. However, most of researches didn't consider results from each pair of channels and different frequency bands.

This research is aimed at investigating relation between EEG signal and emotions by comparing accuracy among each pair of channels and different frequency bands in order to reduce insignificant pairs of channels and frequency bands. All of these are beneficial to the development of emotion classification system using minimal EEG channels in real-time.

II. THEORIES

A. Electroencephalogram (EEG)

Electroencephalogram (EEG) is the recording of electrical activity on the scalp. EEG measures voltage changes resulting from ionic current flows within the neurons of the brain. There are five major brain waves distinguished by their different frequency bands. These frequency bands from low to high frequencies respectively are called Delta (1-3 Hz), Theta (4-7 Hz), Alpha (8-13 Hz), Beta (14-30 Hz) and Gamma (31-50 Hz). Fig. 1 shows the 10-20 system of electrode placement that is an internationally recognized method to describe and apply the location of scalp electrodes. Each site has a letter to identify the lobe and a number to identify the hemisphere location [7], [8].

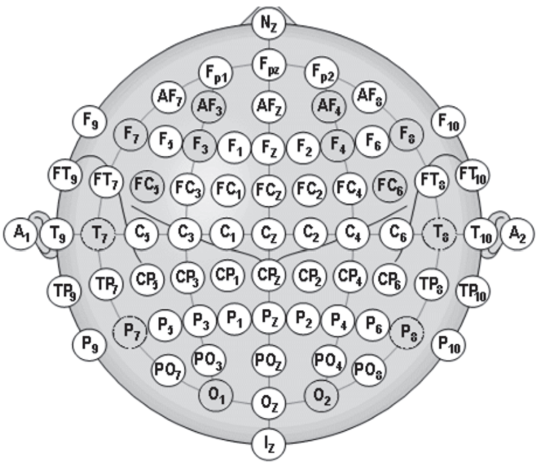

Figure 1. International 10-20 system [7]

B. Model of Emotion

One of the most common models in the emotions field proposes that affective experiences are best characterized by two main dimensions (i.e., Valence and Arousal). The Valence emotion ranges from negative to positive, whereas the Arousal emotion ranges from calm to excited [9]. This model is used in most researches because it is easier to express an emotion in terms of Valence and Arousal rather than basic emotions that can be confused by emotion names [10]. The emotions in any coordinates are shown by facial expression as shown in Fig. 2.

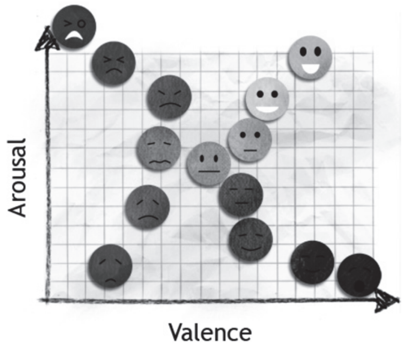

Figure 2. Model of emotion [10]

C. Support Vector Machine (SVM)

SVM is a learning algorithm based on statistical learning theory [11]. The basic training principle of SVM is finding the optimal hyperplane where the expected classification error of test samples is minimized. The optimal hyperplane is the one that maximizes the margins as shown in Fig 3. Maximizing the margins is known to increase the generalization capability. SVM uses regularization parameter (C) that enables accommodation to outliers and allows errors on the training set.

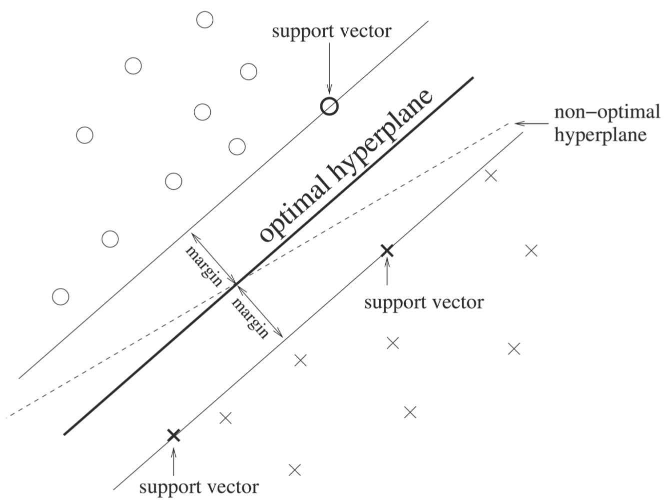

Figure 3. SVM find the optimal hyperplane for generalization [12]

SVM using linear decision boundaries is known as linear SVM. It is possible to create nonlinear decision boundaries by using kernel function $K(x,y)$. The kernel function maps the data to high dimensional feature space and find the optimal hyperplane in that space. The kernel used in this research is Gaussian as shown in (1) where γ is spread of a Gaussian cluster.

$$K(x,y) = \exp(-\gamma\|x-y\|^2) \quad (1)$$

SVM is implemented on several emotion classification researches [4], [5], [6] because of several advantages. SVM are known to have good generalization properties, to be insensitive to overtraining and to the curse-of-dimensionality. Finally, SVM has a few parameters that need to be defined (i.e., C and γ). These advantages are gained at the expense of a low speed of execution [12].

III. Methodology

The process of emotion classification consists of several steps as shown in Fig. 4. First of all a stimulus such as picture, audio and movie is needed. During experiment the participant is exposed to the stimuli to elicit emotion and EEG signal is recorded accordingly. Then artifacts that contaminate EEG signal are removed. This EEG data are analyzed to be extracted the relevant features. Some parts of data are trained to build classification model and the rest of data which are test data are classified using this model to compute accuracy.

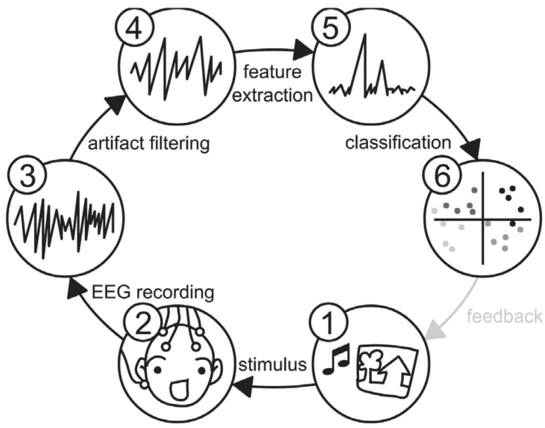

Figure 4. The process of emotion classification [13]

A. Stimulus

The 100 pictures from Geneva Affective Picture Database (GAPED) [14] are used to elicit emotion. The total pictures in this database are 730 that are rated according to Valence and Arousal. We select the highest Valence score 50 pictures to be positive stimuli (i.e., human and animal babies as well as nature sceneries) and the lowest Valence score 50 pictures to be negative stimuli (i.e., human concerns and animal mistreatments).

B. EEG Recording

We use 14 channels EMOTIV [15] (i.e., AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1 and O2) to record EEG signal. Before recording EEG, we wear EMOTIV on the participant for a while to prevent undesired emotions that can arise from unfamiliar or uncomfortable feeling. Then we describe the process of recording and advice participant to stay still to prevent artifact that can occur from moving body. When the participant is ready, we then record EEG and randomly show the 100 pictures that consist of 50 positive pictures and 50 negative pictures to elicit emotion. Each picture shows for 10 seconds. After that, blank screen shows for 5 seconds to adjust participant's emotion. When the 100 pictures are completely shown, the process of recording is end. All these steps take about 30 minutes. There are 11 participants (i.e., 6 men and 5 women) taking part in this experiment.

C. Artifact Filtering

Blind Source Separation (BSS) is used to filter Electrooculogram (EOG) and Electromyogram (EMG) the artifact that contaminate the EEG signal. BSS implementation is done using EEGLAB [16].

D. Feature Extraction

The EEG signals are extracted to 5 frequency bands that are Delta (0-4 Hz), Theta (4-8 Hz), Alpha (8-16 Hz), Beta (16-32 Hz) and Gamma (32-64 Hz) by Wavelet Transform. Then the power spectrum from each band is computed to be the feature. Since EMOTIV have 14 channels, the total features are 70. The features are normalized for each participant by scaling between 0 and 1 to reduce inter-participant variability [4], [5]. We use window for 4 seconds and 50% overlap. Since EEG signal from each picture have 10 seconds, there are 4 samples per picture. Due to 100 pictures, there are 400 samples per participant. Because of 11 participants, the total samples are 4400. All samples are labeled whether positive or negative depending on type of stimulus.

E. Classification

Gaussian SVM with 10-fold cross-validation is used to compute accuracy. The appropriate parameters C and γ are selected by grid-search method. SVM implementation is done using LIBSVM [17].

IV. Results and Discussion

A. Artifact Filtering

We compare accuracy between RAW EEG (EEG signal from direct recording) and BSS EEG (EEG signal after artifact filtering) using all features. We found that BSS EEG gives a better accuracy from 81.18% to 85.41%. As a result, we can conclude that EOG and EMG artifact effect on emotion classification.

B. Varying Pairs of Channels

We compare accuracy among each pair of channels (i.e., AF3-AF4, F3-F4, F7-F8, FC5-FC6, P7-P8, T7-T8 and O1-O2) using all frequency bands. From Fig. 5 we found that pair of F7-F8 gives the highest accuracy at 66.14% and most of frontal pairs give higher accuracy than the other area. As a result, we can conclude that frontal lobe is more related to Valence emotion than the others. This conclusion is consistent with [2], [3].

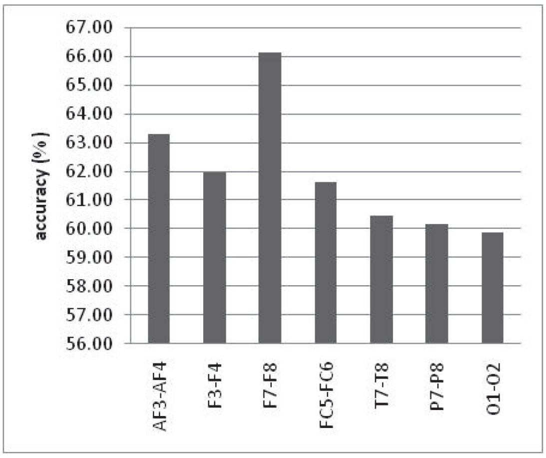

Figure 5. Accuracy from each pair of channels

C. Varying Frequency Bands

We compare accuracy among different frequency bands (i.e., Delta, Theta, Alpha, Beta and Gamma) using all channels. From Fig. 6 we found that Gamma and Beta give accuracy at 81.91% and 80.64% respectively that is clearly higher than the other bands. As a result, we can conclude that high frequency bands are more related to Valence emotion than low frequency bands. This conclusion is consistent with [6], [18].

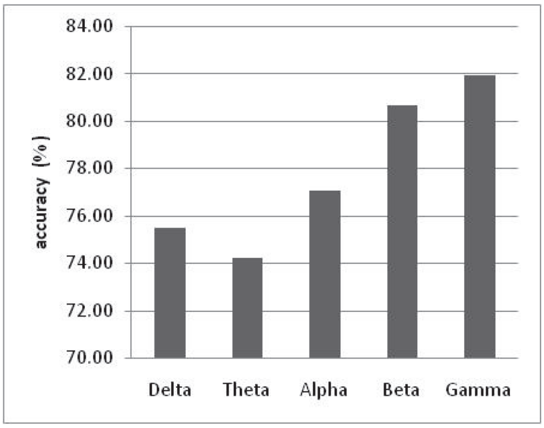

Figure 6. Accuracy from different frequency bands

D. Reducing Pairs of Channels

We compare accuracy when using number of pairs of channels from 1 to 7. We orderly pick pair giving high to low accuracy from the previous result (i.e., F7-F8, AF3-AF4, F3-F4, FC5-FC6, T7-T8, P7-P8 and O1-O2 respectively). From Fig. 7 we found that when using more pairs, it gives higher accuracy. As it reaches 5 pairs, the accuracy becomes nearly stable at 84.18% and when we use all of pairs it gives accuracy at 85.41%. As a result, we can reduce number of pairs of channels from 7 to 5 with almost the same accuracy in order to minimize number of channels.

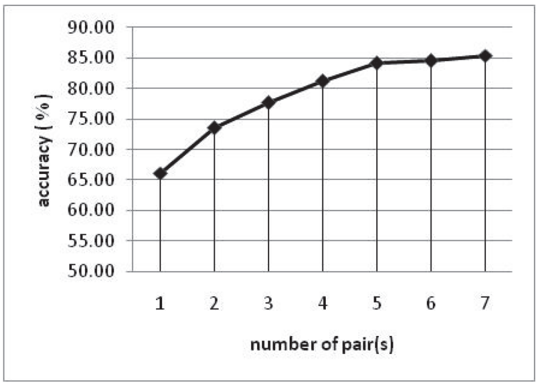

Figure 7. Accuracy from reducing pairs of channels

E. Reducing Frequency Bands

We compare accuracy when using number of frequency bands from 1 to 5. We orderly pick band giving high to low accuracy from the previous result (i.e., Gamma, Beta, Alpha, Delta and Theta respectively). From Fig. 8 we found that when using only Gamma it gives accuracy at 81.91% and when we use more bands it gives a little higher accuracy until 5 bands the accuracy start to decrease. As a result, we can cut low frequency bands such as Theta in order to minimize number of bands.

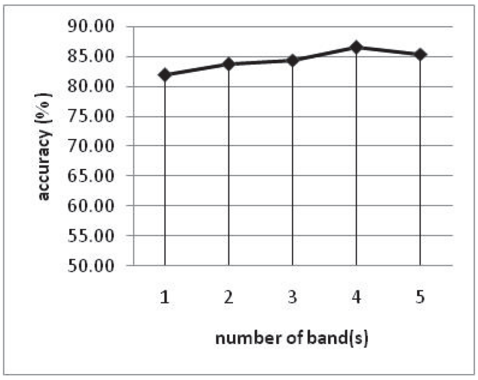

Figure 8. Accuracy from reducing frequency bands

V. CONCLUSION

In this research we use EEG signal to classify two emotions (i.e., positive and negative) elicited by pictures. The power spectrum from each frequency band is used to be the features. The accuracy rate of SVM classifier is about 85.41%. We found that frontal pairs of channels give higher accuracy than the other area especially pair of F7-F8 that gives the highest accuracy at 66.14%. We also found that high frequency bands give higher accuracy than low frequency bands especially Gamma and Beta that give accuracy at 81.91% and 80.64% respectively. Furthermore, we can reduce number of pairs of channels from 7 to 5 with almost the same accuracy and can cut low frequency bands in order to save computation time. All of these are beneficial to the development of emotion classification system using minimal EEG channels in real-time.

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REFERENCES

[1] Gunes, H., & Pantic, M. (2010). Automatic, Dimensional and Continuous Emotion Recognition. International Journal of Synthetic Emotions (IJSE), 1(1), 68-99.

[2] L. A. Schmidt and L. J. Trainor, "Frontal brain electrical activity (EEG) distinguishes valence and intensity of musical emotions", Cognition and Emotion, vol. 15, no. 4, pp. 487–500, 2001.

[3] S. K. Sutton and R. J. Davidson, "Prefrontal brain asymmetry: A biological substrate of the behavioral approach and inhibition systems", Psychological Science, vol. 8, No. 3, May 1997, pp. 204-210.

[4] G. Chanel, J. J. M. Kierkels, M. Soleymani, and T. Pun, "Short-term emotion assessment in a recall paradigm", Int. J. Human-Comput. Stud., vol. 67, no. 8, pp. 607–627, Aug. 2009.

[5] Y. P. Lin, C. H. Wang, T. L. Wu, S. K. Jeng, and J. H. Chen, "Support vector machine for EEG signal classification during listening to emotional music", in Proc. IEEE Int. Workshop Multimedia Signal Process., Queensland, Australia, 2008, pp. 127–130.

[6] Nie, D., Wang, X.W., Shi, L.C., Lu, B.L.: EEG-based emotion recognition during watching movies. In: The Fifth International IEEE/EMBS Conference on Neural Engineering, pp. 186-191. IEEE Press, Mexico (2011).

[7] Sharbrough F, Chatrian G-E, Lesser RP, L ders H, Nuwer M, Picton TW (1991): American Electroencephalographic Society Guidelines for Standard Electrode Position Nomenclature. J. Clin. Neurophysiol 8: 200-2.

[8] Ernst Niedermeyer, Fernando Lopes da Silva, Electroencephalography: Basic Principles, Clinical Applications, and Related Fields.

[9] Russell, J. A. (1980). "A circumplex model of affect". Journal of personality and social psychology 39 (6): 1161–1178.

[10] R. Horlings, "Emotion recognition using brain activity", Department of Mediamatics, Delft University of Technology, 2008.

[11] V. Vapnik, "The Nature of Statistical Learning Theory", Springer, 1995.

[12] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi. A review of classification algorithms for EEG-based brain-computer interfaces. Journal of Neural Engineering, 4:R1–R13, 2007.

[13] D. Bos, "EEG-based emotion recognition", [Online]. Available : http://hmi.ewi.utwente.nl/verslagen/capita-selecta/CS-Oude_Bos-Danny.pdf [Access 1 March 2013].

[14] Dan-Glauser, E. S., & Scherer, K. R. (2011). The Geneva affective picture database (GAPED): a new 730-picture database focusing on valence and normative significance. Behavior Research Methods, 43(2), 468-477.

[15] "Emotiv EEG Neuroheadset", [Online]. Available : http://emotiv.com/upload/manual/EEGSpecifications.pdf [Access 1 March 2013].

[16] Delorme A & Makeig S (2004) EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics. Journal of Neuroscience Methods 134:9-21.

[17] Chih-Chung Chang and Chih-Jen Lin, LIBSVM : a library for support vector machines. ACM Transactions on Intelligent Systems and Technology, 2:27:1--27:27, 2011.

[18] M. Li, and B. L. Lu, "Emotion classification based on gamma-band EEG", IEEE Int. Conf. Engineering in Medicine and Biology Society, Minneapolis, 2009, pp. 1223-122.