Emotion Classification using Brainwave

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***Abstract*— Emotions have an indispensable role in human life to reflect a human interaction. It is an important role in the aim of media design, be it videos, music, or games, to understand more about user. In the interaction between human and media is significant issue, this can be measure honesty and continuity by using physiological signal, especially, Electroencephalogram (EEG). EEG is an electrical activity from voltage in the brain or brainwave. It was used to evaluate consumer satisfaction that is one way of neuromarketing in action. In this paper classify three kinds of emotions, positive, neutral and negative on valence scale in emotional dimensions, stimulus by video clip. The EEG collections are selected by power spectral density (PSD) as a feature. The data are stratified 10-fold cross validation and compare with four classifiers, namely support vector machine (SVM), k-nearest neighbors (KNN), naïve Bayes and decision tree (DT), to explore the appropriate algorithm to classify emotion using brainwave. The best accuracy in positive and negative emotion is SVM, and the best accuracy in neutral emotion is DT. The average test accuracy in three emotions of 91.67% is SVM. All of these are beneficial to develop emotion classification system for conduct experience design while users interact with media.**

Keywords—classification; emotion; electroencephalography; valence; neuromarketing

I. INTRODUCTION

Emotion is a complex phenomenon in the daily life of human to reflect a mental state and psychophysiological expression. The emotional researches make practical use the various aspects such as emotional disorders [1], military psychiatry [2], emotional marketing [3] and emotional advertising [4]. Researchers define emotions according to more dimensions, but only valence dimensions were selected in this experiment. In psychology, valence means attractiveness (positive valence) or averseness (negative valence) of the situation [5]. There are ways to study of emotional detection in prototype testing such as questionnaire, interview, observation, etc. after the prototype testing. It is not immediately and emotions not always giving feedback effectively differ from physiological signal such as electrocardiogram (ECG), facial electromyogram (EMG), skin conductance and, especially, EEG. EEG is signals that satisfy to measure valence emotion. It indicates brain activity in each emotional state, but there are complicated and difficult to understand. So, a classification method is one of the most important parts of this system.

There are several classification methods to classify emotional states. SVM is popular classifier, was selected by researchers. Noppadon and friends use SVM to classify happy and unhappy state [15], likewise, S. Liu and friends use SVM to classify positive, neutral and negative emotion [16]. Moreover, KNN, DT, MLP, etc. are use in several researches of emotional classification.

Several classification methods have been studied to map the electrical activity of the brain to specific category of emotion. In this paper, the algorithms were selected from simple and popular classification algorithm, namely, SVM, KNN, naïve Bayes and decision tree. It is considered to research performance and accuracy in different classification algorithms in order to get more response with continuous available, an honest answer, increase accurate for market research, save time and cost of research surveys, engage with your target audience and be an option to decision making that is appropriate for the evaluation.

II. BACKGROUND

A. Emotion

Internal and external stimuli were used to trigger positive and negative emotions that show in smooth muscles changing, viscera and gross behavior [6]. Emotion has separated into six types of human emotions are fear, surprise, sadness, disgust, anger, joy by Paul Ekman after that Robert Plutchik increase anticipation and acceptance into the primary emotion of human. Eight emotions are entire into emotion wheel and presented as combinations of primary emotions [7].

Emotions are various and complex then Cynthia Breazeal [8] represents to 3D emotion space by transforming emotions into 3 parameters: arousal, valence and stance. It assists to understand basic human emotion as shown in figure 1.

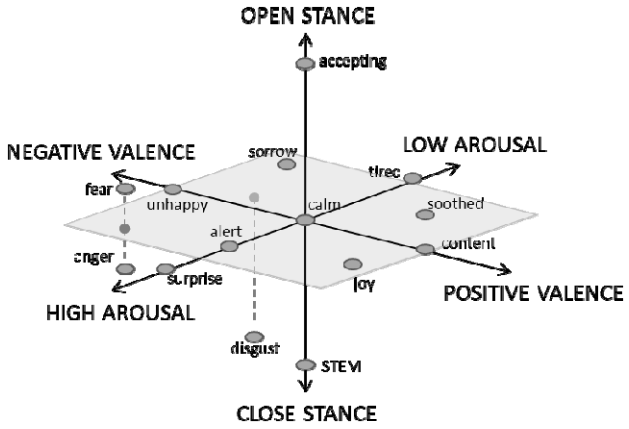

Figure 1 3D emotion space

IAPS (International Affective Picture System) is developed by Lang and Breadley [9]. It is a picture corpus that studies emotion responses and using SAM estimation. SAM was selected as valence estimation between 1 and 9 (1 = negative, 5 = neutral and 9 = positive) as shown in figure 2.

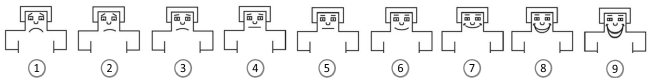

Figure 2 SAM (valence scale)

CLASSIFICATION & SUB-BAND FREQ

B. *Electroencephalography*

There are a huge number of neurons in brain. Neurons communicate with each other by sending chemicals, called neurotransmitters, across a tiny space, called a synapse, between the axons and dendrites of adjacent neurons. The measurement and the recording of electrical pulses in the brain called electroencephalography (EEG).

Epoc from Emotiv was chosen as the EEG device for our experiment. Analysis of EEG signal is observed in frequency bands that be divided into 5 groups: theta (4 – 8 Hz), alpha (8 – 12 Hz), low beta (12 – 16 Hz), high beta (16 – 25 Hz) and gamma (25 – 45 Hz). Epoc is used more research such as a study on non-invasive brainwave optimization, studied the efficacy of EEG and found emotion occur when stimuli are stimulated [10], and brain dominance using brainwave signal, studied the relation between emotions and brain activities that shown left and right frontal lobe are most emotionally measurable [11].

C. *Classification*

Patterns of brain activities are difference as individuals, so EEG classification methods are necessary to choose the most suitable and effective. Classification algorithms were selected from well-known is SVM, KNN (when k=1, k=3 and k=5), naïve Bayes and decision tree.

Different methods have different advantages and disadvantages. For example, SVM is used to separate input vector, KNN using distance between points to cluster data, naïve Bayes is probabilistic classifiers based Bayes theorem and decision tree is used to predict output from observation that represented in the branches.

The review of emotion classification using brainwave is various. For instance, Robert, Dragos and Leon [12] provided the relation between brain activities and IAPS using SAM estimation divided into 5 levels and used neural networks, SVM and naïve Bayes to classifier. Results indicated that SVM is the best accuracy, valence accuracy is 32% and arousal accuracy is 37%. To more delicate, divide scale to 2 levels (level 1 and 5) that show valence rates were 71% and arousal rates were 81%. In other research provided emotion impact on brain activity while listening to music and comparison of SVM, multi-layer perceptron (MLP) and decision tree classification. Analysis revealed that SVM is the best accurate of classification [13]. Moreover, SVM has less overfitting than other algorithm [14].

III. METHODOLOGY

The process of brainwave classification are sampling and modeling. Firstly, the sampling process was tested in 5 male subjects aged 20 – 24 years (average = 22.2, SD = 0.45) and used Epoc in 4 channel (F7, F8, T7, T8) for retrieve EEG data and 2 reference (CMS, DRL) as shown in figure 3.

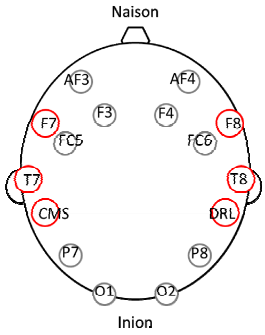

Figure 3 EEG Electrode Placements

We used 6 videos for stimulator. Videos were chosen referable IAPS for identifying positive and negative emotions. The first video will prepare the subject calm state, moreover, are stored in each emotional range after that use SAM-Rating-Scale for valence. Each video has sequence of experiment as shown in figure 4.

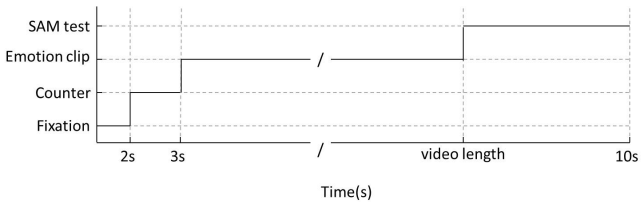

Figure 4 Experimental Series

After experiment, we get data in three data set, namely negative (10% of total), neutral (65% of total) and positive (25% of total).

A. *Feature extraction*

Features are extracted from EEG signals after data, cause emotion, were cropped by hand and were performed MATLAB and annotated data labeled to each record of EEG signal. Data are implemented with a sliding window technique to the sequential data to retrieve more data.

Then normalize data and selected 11 features (maximum, minimum, median, mode, arithmetic mean, power, standard deviation, first deviation, normalized first derivative, normalized first derivative, second derivative and normalized second derivative) based on time domain, as show equation below:

Arithmetic Mean: $\mu = \frac{1}{N}\sum_{n=1}^{N} x_n$ (1)

Power: $P = \frac{1}{N}\sum_{n=1}^{N} |x_n|^2$ (2)

Standard Deviation: $\sigma = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(x_n - \mu)^2}$ (3)

First Derivative: $\delta = \frac{1}{N}\sum_{n=1}^{N-1} |(x+1) - x|$ (4)

Normalized First Derivative: $\bar{\delta} = \frac{\delta}{\sigma}$ (5)

Second Derivative: $\gamma = \frac{1}{N-2}\sum_{n=1}^{N-2} |(t+2) - t|$ (6)

Normalized Second Derivative: $\bar{\gamma} = \frac{\gamma}{\sigma}$ (7)

In classification method, we use 11 features from 5 band frequencies and 4 channels (F7, F8, T7 and T8).

B. *Emotion Classification*

Emotions are classified into 3 classes: negative (valence at 1 – 3), neutral (valence at 4 – 6) and positive (valence at 7 – 9). For classification, we created valence class distinctly by different classifying algorithms: SVM, k-NN (k=5), k-NN (k=3), k-NN (k=1), naïve Bayes and decision tree. All classification in performed by using WEKA.

IV. Experimental Result

A. *Measurement*

From the collection of experiments, 6758 data were selected clearly (positive 25%, neutral 65% and negative 10%) after that classified by 10 – fold cross validation, then estimate from confusion matrix and accuracy of equation (8) – (11)

Precision: $PPV = \frac{tp}{tp+fp}$ (8)

Recall: $TPR = \frac{tp}{tp+fn}$ (9)

F-Measure: $F_1\ score = \frac{2 \times PPV \times TPR}{PPV + TPR}$ (10)

Accuracy: $ACC = \frac{t \times 100}{N}$ (11)

When PPV is the number of positive predictive value

TPR is the number of true positive rate

ACC is the number of accuracy value

tp is the number of true positive cases in the data

fp is the number of false positive cases in the data

fn is number of false negative cases in the data

t is the number of correct classification

N is the total number of samples

B. *Result & Discussion*

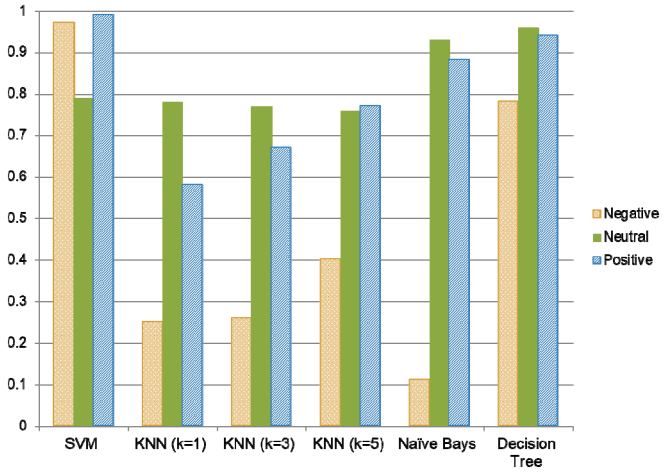

Figure 5 Experimental Results

Figure 5 shows the efficiency of the classification method. When evaluating system performance with f-measure, SVM is the most effective in negative and positive emotion and decision tree is the most effective in neutral emotion. SVM accuracy in negative and positive emotion is 97% and 99% while naïve Bayes is the lowest accuracy of negative emotion classification and KNN is the lowest accuracy of positive emotion classification that is 11% and 58%. In neutral emotion, decision tree accuracy is 96% and the lowest is KNN that is 76%. Accurate comparison with these data that show decision tree is the highest accurate classification (93.95%) because neutral data have the most and negative data have the least. In overall, the average test accuracy in three emotions of 91.67% is SVM.

V. Conclusion

The performance and accuracy in different classification algorithms for identify positive, neutral and negative emotion using Epoc device to measure brainwave during subject while watching video. Emotional dataset to preliminary processing, then are extracted feature prepare for classification method. This research use SVM, KNN, naïve Bayes and decision tree is classifiers. The comparative average results of this study revealed SVM algorithm is the most effective, rate are 91.67%. Although SVM is the most effective performance of classification, but have other factors are too important for your work. The pedagogical implications of the study that video are selected to be a stimuli cannot separate clearly the emotion. In the future, the system should be able to process in real time, increase the response to consumer immediately.

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REFERENCES

[1] A. Panat and A. Patil, "Analysis of emotion disorders based on EEG signals of Human Brain," IJCSEA, vol. 2, pp. 19-24, August 2012.

[2] W. Khuangsirikul, "Military Psychology," Psychiatric Association of Thailand, vol. 56(4), pp. 339-344, October-December 2011.

[3] P. Kotler, H. Kartajaya, and I. Setiawan, Marketing 3.0: From Products to Customers to the Human Spirit. Hoboken, N.J. : Wiley, 2010.

[4] N. Hollis. "Emotion in Advertising: Pervasive, Yet Misunderstood," Milliward Brown, 2010.

[5] N. H. Frijda, The Emotions. Cambridge (UK): Cambridge University Press, 1986. p.207

[6] C. Breazeal, "Emotion and Sociable Humanoid Robots," International Journal of Human-Computer Studies – Application of affective computing in human-Computer interaction, vol. 59, pp. 119-155, July 2003.

[7] Plutchik, Robert (1980), Emotion: Theory, research, and experience: Vol. 1. Theories of emotion, **1**, New York: Academic

[8] C. Breazeal, "Emotion and Sociable Humanoid Robots," 2002.

[9] P. J. Lang and M. M. Bradley, "Emotion and the motivational brain," Biological psychology, vol. 84, no. 3, pp. 437-450, 2010.

[10] S. Jia-Wei and W. C. Siew, "A study on non-invasive brainwave optimization," in International Conference on Software Intelligence Technologies and Applications & International Conference on Frontiers of Internet of Things 2014, 2014, pp. 27 – 32.

[11] M. Mustafa, N. Hamid, N. Abdullah, R. Samad, and D. Pebrianti, "Brain dominance using brainwave signal," IEEE International Conference on Control System, Computing and Engineering (ICCSCE), 2015, pp. 298-302.

[12] R. Horlings, D. Datcu and L. J. M. Rothkrantz, "Emotion Recognition using Brain Activity," International Conference on Computer Systems and Technologies (CompSysTech), 2008, pp. II.1-1-II.1-6.

[13] N. Thammasan et, K. Moriyama, K. Fukui and M. Numao, "Continuous Music-Emotion Recognition Based on Electroencephalogram," IEICE Transactions on Information and Systems, vol. E99.D, no. 4, pp. 1234-1241, 2016.

[14] P. Thamrongrat, "Web page Classification Using Feature Reduction And Support Vector Machine," M. S. thesis, Prince of Songkla University, Songkla, 2009.

[15] N. Jatupaiboon, S. Pan-ngum, and P. Israsena, "Emtoion classification using minimal EEG channels and frequency bands," in JCSSE, 2013, pp. 21-24

[16] S. Liu, J. Tong, M. Xu, J. Yang, H. Qi, and D. Ming, "Improve the generalization of emotional classifiers across time by using trainning samples from different days," in IEEE EMBS, 2016.

[17]