Emotion Detection Using Physiological Signals EEG & ECG

[1]Amjad M.R. AlzeerAlhouseini, [2]Imad Fakhri Al-Shaikhli, [3]Abdul Wahab bin Abdul Rahman,
[4]Mariam Adawiah Dzulkifli
Department of Computer Science, IIUM, Malaysia
Department of Psychology, IIUM, Malaysia
[1]amjadm2008 @gmail.com
[2]imadf@iium.edu.my
[3]abdulwahab@iium.edu.my
[4]m.adawiah@iium.edu.my

Abstract

Emotion modeling and identification has attracted substantial interest from disciplines including computer science, cognitive science and psychology. Despite the fact that a lot of qualitative studies have been carried out on emotion, less investigated aspects include the quantifying of physiological signals. This paper presents two physiological signals which are ECG and EEG and shows analysis of its emotional properties. A solution based on the short Fourier transform is proposed for the recognition of dynamically developing emotion patterns on ECG and EEG. Features extraction that are used in this paper are Kernel Density Estimation known as (KDE) and Mel-frequency cepstral coefficients known as MFCC. The classifier that is used in this work is Multi-layer Perceptron known as MLP, classification features are based on the valence and arousal. The experimental setup presented in this work for the elicitation of emotions is based on passive valence /arousal. The results shows that the ECG signal has direct relationship with the arousal factor rather than the valence factor. Also, EEG signal using 19 channels reported high accuracy results for determining emotions.

Keywords*: Electroencephalogram, Electrocardiogram, Human Emotions, MFCC, KDE.*

1. Introduction

Emotions are associated with every activity in our everyday life, playing a major part in non-verbal communication. Feelings may also affect the area of the brain that regulates thinking, reasoning, and decision. Deep emotions have specific physical reactions for instance raising the heart rate, face flushing, increasing the rate of the inhaling and exhaling, and increasing hypertension that are moving effects. There are numerous distressing elements that affect human's attention[1]–[5]. In the past studies, researchers have proven that people in the negative and oftentimes positive psychological states may be diverted. Negative emotions are the reactions of the individual as a result of stressing situation. While positive emotions are the reactions of the individual as a result of happy and calm situations. Therefore, being able to quantify emotions is vital to the understanding of individual conduct. To develop a smart man-machine interface system that understands non-verbal details, for instance desire, feelings and emotions of individual, this research work aims to deliver an emotion detection system by using pattern recognition and classification methods.

Electroencephalography (EEG) calculate each of the amplitude and frequency of electrical pulse produced by the human being brain[6]. The advantages of making use of EEG to carry out experiments that are non-invasive, straightforward, fast, and low-cost. It is neither hurtful nor distressing or time-consuming for the participants. Hence, EEG has turned into a desired technique in examining the brain's reactions to emotional stimulus [7]–[11]. In this research work, a very common neural network has been applied to the EEG and ECG signals' frequency domain data, to be able to establish the suitable selection of parameters. The parameters can be derived by conducting several experiments on different subjects; some of these parameters are the overlapping rate, sampling length. The selection of parameters is normally much better and insightful this way. Lastly, research experiments are carried out to find significant characteristics that classify the 4 various emotions (Happy, Clam, Sad, and Fear).

The initial step in modeling any phenomenon is data gathering. The experiment design is a vital step in acquiring meaningful data, therefore we need to institute methods that effectively stimulate emotions in a lab environment where we can record and gather meaningful data. In quantifying psychological actions we are restricted to the study of observable expressions like vocal traits, gestures, facial expressions. These strategies are well-known in HCI as they make use of the same hints that people depend upon to identify and figure out emotional states. Furthermore, the majority of people exhibit similar expressions as a result of identical psychological stimuli that enables objective emotion notation[12].

The main disadvantage to applying attitudinal strategies for emotion recognition is the skepticism that develops in the event of folks who either are knowingly controlling their emotional expressions or are normally suppressive. For example, even though facial expressions may be examined to find out emotions, there is no certainty a person will convey the related cue, regardless of whether they are going through a specific emotion. Therefore, this has critical ramifications in some applications for instance surveillance.

The rest of this work is structured as follows: Section 2 gives a summary of the related work on emotion recognition, with specific interest in the works that applied EEG and ECG. The methodology of deriving emotions from EEG and ECG is presented in section 3. The feature extraction and classification are discussed in the subsequent sections. The rest of the paper discusses the performance of the framework. Lastly, we conclude with a summary of our results as well as the viewpoints for future work.

2. Related Work

An intriguing option to the application of conduct modalities is the bio signal signals that make up essential signs of the body. Forms of this category range from the, electromyogram (EMG), electroencephalogram (EEG), galvanic skin response (GSR), electrocardiogram (ECG), heart rate (HR), blood volume pressure (BVP) or heart rate variability (HRV). These bio signals have typically been employed for medical diagnostics, but there is substantial proof to point out that they are responsive to and may relay details about psychological states [13]–[18]. One of the advantages of recognizing emotions and feelings using physiological signals is that these are unconscious responses of the human body, and therefore are very difficult to conceal. Furthermore, during the time that the electrodes are connected to the human body, these signals are captured constantly, permitting regular psychological analysis. This is not the scenario with verbal features, for instance, that may only be recorded while the person is conversing.

In addition to the open theoretical issues, there are practical challenges as well. The experimental setup are much more sophisticated compared with behavioral emotion investigation, where the data gathering is assisted by showing the participants to demonstrate emotions. For EEG and ECG testing more complex techniques are required to generate genuine feelings in a lab environment. Additionally, marking physiological signals is very subjective and, therefore, very risky as a result of complexity in developing the ground truth. An additional practical obstacle pertains to signal acquisition.

The data gathering process is more invasive in comparison to that for conduct modalities because the electrodes have to be in touch with the skin throughout a recording period. Because of this, it is crucial to reduce the number of information needed for this particular task, i.e., for recognition to depend on as few signals as you can.

3. Methodology

3.1. Electrodes Placement

For EEG electrodes placement, 19 channels or electrodes were put on the scalp of the subjects (P4, O2, P8, T8, C4, Cz, Fz, F4, Fp2, F8, Fp1, F7, F3, C3, T7, P7, P3, O1, Pz). The electrodes were placed using the International 10-20 standard system.

Figure 1 shows the block diagram for analyzing the raw EEG signal. First, the sent through filters to remove the artifacts. Then, the features are extracted using MFCC and KDE. Finally, the featured are classified using MLP.

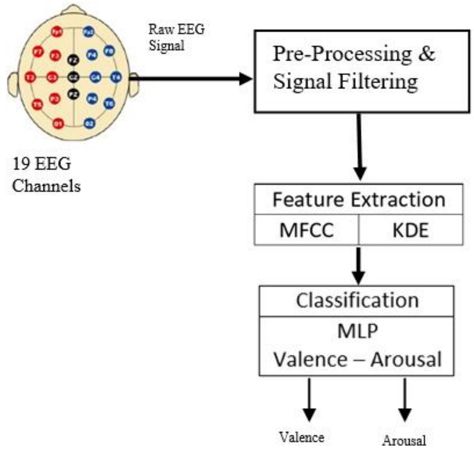

Figure 1. Block Diagram for EEG Analysis

For ECG electrode placement, 3 electrodes were attached to the body surface of the subject; 1 electrode is attached to the right wrist, 1 electrode is attached to the left wrist and 1 electrode is attached to the left leg. This placement is known as Lead II placement which taken from the standard 12 lead placement.

Figure 2 demonstrate the block diagram for analyzing the raw ECG signal acquired from the subjects. The signal is pre-processed and the noise is removed through band pass filter. Then the signal is segmented and short Fourier transform is applied. KDE and MFCC act as feature extraction. Finally, MLP is employed as classifier.

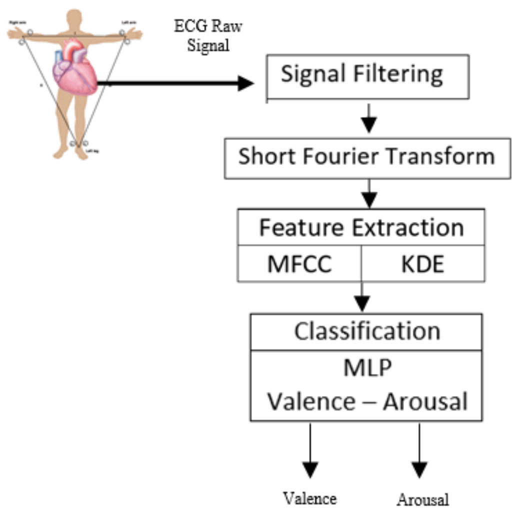

Figure 2. Block Diagram for ECG Analysis

3.2. Feature Extraction

Mel frequency cepstral coefficients (MFCC) and kernel density estimation (KDE) were used for feature extraction in this study. These are normally employed in waveforms dimension minimization applications. A melcepst tool is employed to compute the cepstrum of the signal. We have employed 12 MFCC coefficients to acquire the appropriate features of the EEG and ECG.

The MFCC feature extraction method is widely used in speech recognition applications. However, by tuning the parameters to suit our needs, the MFCC may yield better performance and accuracy than the KDE. Figure 3 shows a block diagram for a conventional MFCC implementation.

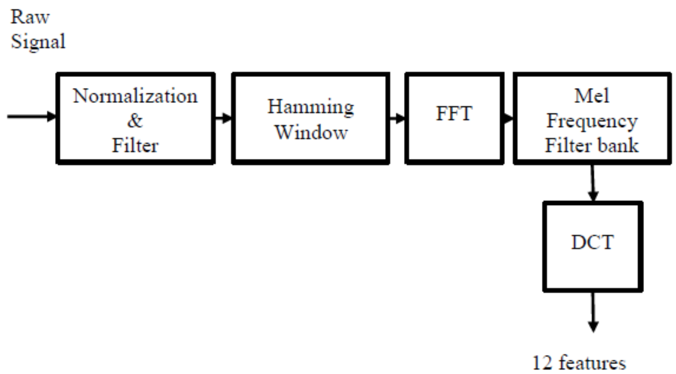

Figure 3. Block Diagram for MFCC Algorithm

Melcepst computes the cepstrum of the wave. The mel frequency can be calculated using the following formula:

$$fmel = 1127 \ \log_n(1 + finn/700)$$

The kernel density estimate (KDE) is the most common nonparametric method for density estimation [19] and is the second feature extraction method applied to the pre-processed EEG signals in this study. The results of this feature extraction are then compared with those of the MFCC for performance analysis. The KDE computes a probability density estimate by applying the following formula:

$$\hat{f}_h(X) = \frac{1}{n}\sum_{i=1}^{n} K\left(\frac{x - x^i}{h}\right)$$

$$\hat{f}_h(X) : is\ symmatric\ function\ that\ integrate\ to\ one.$$
$$h > 0 : is\ the\ bandwidth\ window\ or\ smooting\ paramenter$$

3.3. Classification

The final step in this procedure is the classification of the extracted features having a purposeful and yet effective classifier. Multilayer perceptron (MLP) technique has been selected to categorize the features in order that it can obtain the pre-emotion of the subject which refers to the participant emotion responses. The neural network architecture, MLP with feed forward routes groups the input data onto a set of relevant output. Selecting the right parameters for the number of layers and the number of neurons required for MLP structure is important to make sure a good result come out. Dataset given into the input layer are the 228 features extracted from the MFCC and KDE stage respectively. Each of the input is processed by the MLP by computing the product of input data with its assigned weights in the hidden layers. In this research work, 0.1 was set as the mean square error (mse) having a one hidden layer composed of 10 neurons. Furthermore, the tan-sig was used as the activation function and purelin as the output layer with 0.01 learning rate.
In the experiments, eyes close and eyes open data were collected to establish a baseline and determine the pre-emotion or baseline emotion. The data acquired from the individuals are analyzed from the emotion data of calm, happy, sad, and fear.
In order to obtain well-performing outcomes having a high percentage of precision, the k-fold cross-validation is used for the global validation. K-fold cross-validation develops the notion of rotation screening in a clever method by revolving data through the process. Dataset is once again split

arbitrarily into sets, however k equal-sized sets are employed. The train-test procedure is done again k times, every time making another part of the dataset out as the test set. The data and its preferred output are randomized and divided into five folds which imply that the procedure is repeated 5 times. This is necessary to take away any biases from the data[20]. The dividing procedure helps to have various training and testing data.

3.4. Experimental Design

Twenty participants are briefed on the experiment setup and were asked to sign a consent form for taking part in experiments. Then, participants were asked to sit down in a quiet, and controlled room. Prior to the data gathering, each participant is made familiar with the experiment procedure. After that, the sensors are positioned on the head of each participant and also sensors are placed on the terminals of the body. Data collection is obtained by a machine called Brain Marker. At first, participants are asked to close their eyes for 1 min and then open for 1 min. afterwards, the picture clips with four basic emotions are displayed to them for 1 min per picture clip. Lastly, the captured brain signals are saved for later on analysis.

3.5. Stimulus

In this paper, we have made use of the picture clips with pictures showing emotions to elicit emotional reactions. The subjects were exposed to four basic emotions, the International Affective Picture (IAPS) is employed to generate emotional reactions [21].

4. Result and Discussion

In this section, the results of the memory, homogenous and heterogeneous tests are discussed in detail. Furthermore, the level of accuracy of emotion detection based on valence and arousal is explored in detail. All the tests employed in this study used fivefold cross validation to obtain robust results.
Valence and arousal are two factors in the affective space model used to determine emotions. Therefore, extracting the corresponding valence and arousal of each subject is important to ensure effective results. The two feature extraction algorithms (MFCC and KDE) were used here to determine the best accuracy for each method. Hence, the MFCC and the KDE algorithms are used in the memory and homogenous test analysis.

4.1. Memory Test Result

The memory test using the KDE for EEG signals is depicted in Figure 4. Although the KDE algorithm achieved high accuracy in the memory test, it did not perform well in the homogenous test based on fivefold cross validation. This is because in the memory test, the MLP learned the entire dataset and tested on the same dataset, while in the homogenous test, the MLP learned 80% of the dataset and was tested with the other 20%.

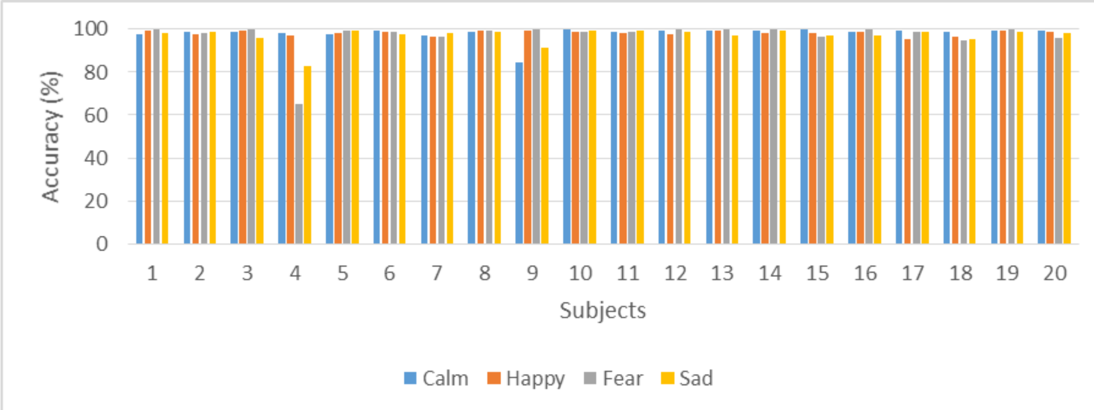

Figure 4. Accuracy of Emotions based on the KDE using Memory Test for EEG signal

Figure 5 shows the results of the memory test for the ECG signals. The overall average accuracy for 19 subjects is 68%, which is slightly higher than the homogenous test results (66%). The results of the memory test using the MFCC are shown in Figure 6. The overall accuracy of the memory test for the 20 subjects is 83.90%.

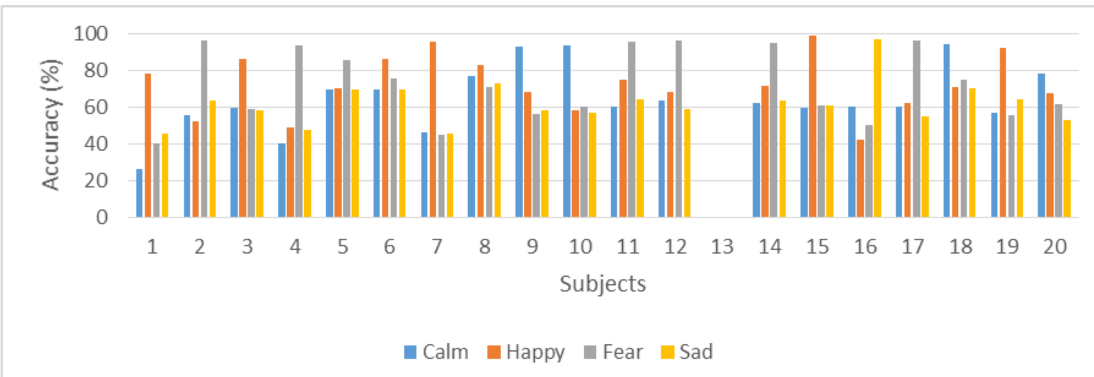

Figure 5. Accuracy of Emotion Detection based on the KDE using the Memory Test for ECG signals

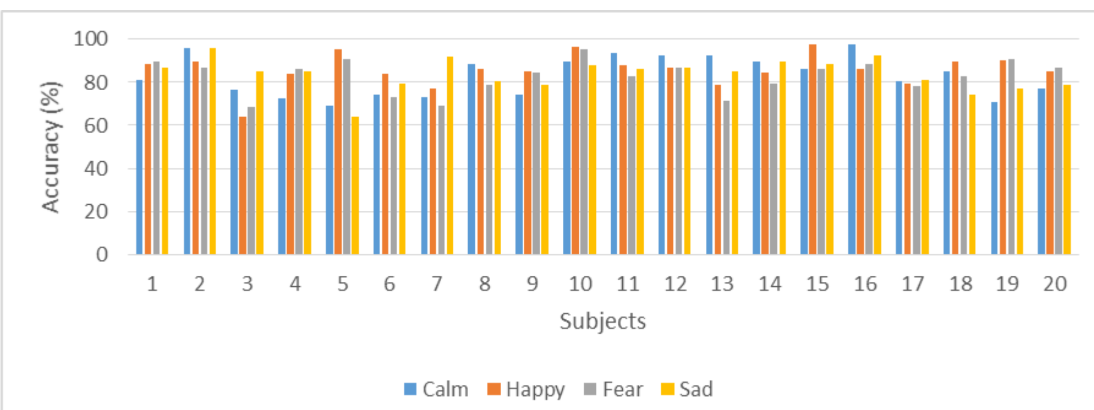

Figure 6. Accuracy of Emotion Detection based on the MFCC using the Memory Test for EEG signals

4.2. Homogenous Test Result

The homogenous test is based on slicing the dataset into 5 folds for each subject. To generate the network classifier, 80% of the data are fed to the MLP while the other 20% are used for testing. For the MFCC, 228 features with 98 instances were fed to the MLP for training, and 228 features with 25 instances were used for testing. For the KDE, 1900 features with 397 instances were sent to the MLP for training and generating the classifier, and 1900 features with 99 instances were used for testing the classifier. Accuracy is expected to be lower for the homogenous test than for the memory test because the MLP did not learn the entire dataset.

Figure 7 shows the degree of accuracy of extracting the four basic emotions for 20 subjects using the KDE. The minimum accuracy for this test is 25% (4 emotions, each emotion should be at least 1/4 or 25%). When using the KDE, the classifier was unable to recognize happy stimuli accurately; it reported less than 25% for the happiness emotion for 10 subjects.

On the other hand, the MFCC outperforms the KDE. It successfully managed to identify the 4 basic emotions for 20 subjects as shown in **Error! Reference source not found.**. When using the MFCC, the classifier reported a minimum accuracy of 64.23% for subject number 17 for the happiness emotion (higher than 25%) and a maximum accuracy of 97.56% for subject 16 for the calm emotion. The average accuracy for the calm emotion using the KDE was 86.89%, while when using the MFCC it was 81.26%. The average accuracy for the happiness emotion using the KDE was 29.63%, while when using the MFCC it was 81.54%. Note the significant gap between the performance of the KDE and MFCC when identifying the happiness emotion. The overall accuracy of the MFCC for identifying the four basic emotions was 81.51%—higher than the overall accuracy of the KDE, which was 71.31%.

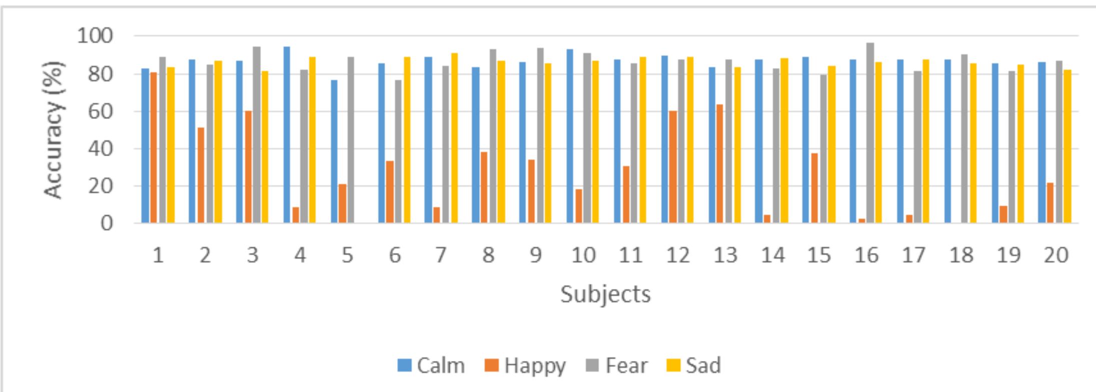

Figure 7. Accuracy of Emotion Detection based on the KDE using the Homogenous Test for EEG signals

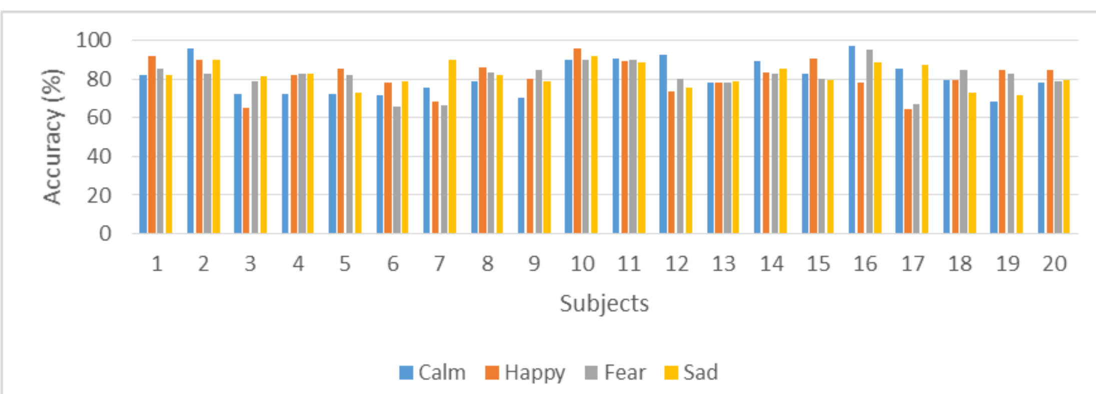

Figure 8. Accuracy of Emotion Detection based on the MFCC using the Homogenous Test for EEG signals

Figure 9 shows the accuracy of emotion identification using the homogenous test for the ECG signal. In the homogenous test, a network classifier is constructed for each subject to identify his or her emotions individually. The minimum accuracy for each emotion is 25%. The classifiers successfully identified the 4 basic emotions for each subject because they achieved better than 25% for all subjects. However, the data for Subject 13 was missing after the experiment was complete due to human error. The overall average accuracy of the classifier is 66.11%. Obviously, the results of the EEG homogenous test are higher than the results of the ECG homogenous test. Therefore, EEG signals are more reliable than ECG signals.

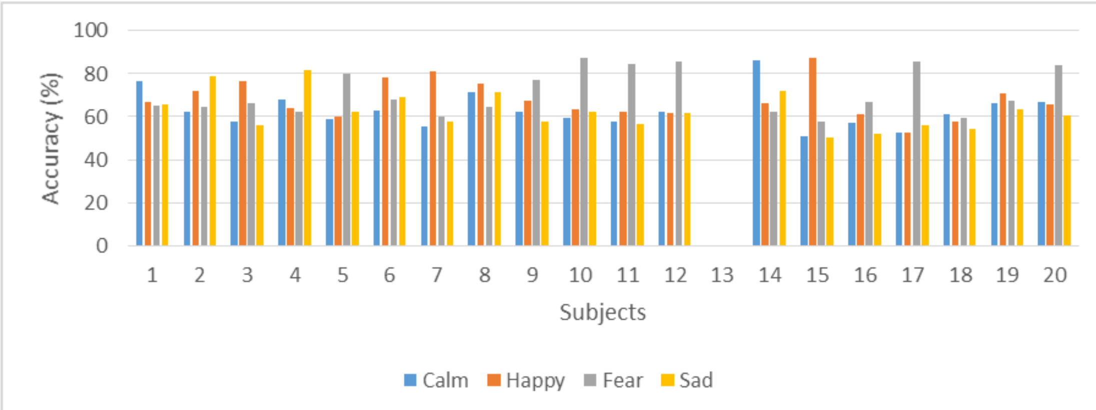

Figure 9. Accuracy of Emotion Detection based on the KDE using Homogenous Test for ECG signals

4.3. Heterogeneous Test Result

Figure 10 shows the accuracy of emotion detection based on the KDE using the heterogeneous test for the ECG signals. In the heterogeneous test, a network classifier is constructed using all the emotion data for all subjects; the classifier is trained and tested using fivefold cross validation. It is interesting to see the high accuracy for the emotion of fear in all subjects. This indicates that the emotions extracted from ECG signals have a strong relationship with the arousal factor rather than the valence factor.

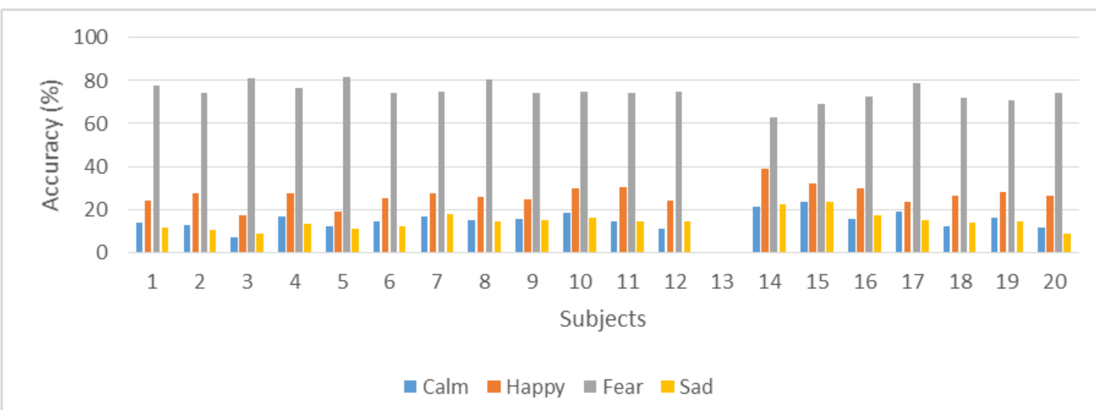

Figure 10. Accuracy of Emotion Detection based on the KDE using the Heterogeneous Test for ECG signals

5. Conclusion and Future Work

Emotion detection based on EEG and ECG signals is highly dependent on the collection of meaningful data. It is difficult to design an experimental setup that can produce the same emotion in every subject, especially when the same stimuli are used for all subjects. Different individual characters, varying moods, and the lack of ability to accurately self-report an emotional experience may significantly affect the outcome of a study. The ECG signal has a direct relationship with the arousal factor. However, the signal could not determine the valence factor. Emotion extraction for EEG signal using MFCC reported higher results than KDE algorithm. The ECG data were short; only one channel was used to record the ECG signal (hardware limitation) and the data were recorded for one minute only. In future work, we seek to improve the accuracy of emotion detection using ECG signal since the ECG signal is not reliable to report four basic emotions.

6. References

[1] M. Li, Q. Chai, T. Kaixiang, A. Wahab, and H. Abut, “EEG Emotion Recognition System,” in *In-vehicle corpus and signal processing for driver behavior*, Springer, 2009, pp. 125–135.

[2] M. Othman, A. Wahab, I. Karim, M. A. Dzulkifli, and I. F. T. Alshaikli, “EEG Emotion Recognition Based on the Dimensional Models of Emotions,” *Procedia - Soc. Behav. Sci.*, vol. 97, pp. 30–37, Nov. 2013.

[3] A. M. R. A. Alhouseini, I. F. Al-Shaikhli, A. W. B. A. Rahman, K. Alarabi, and M. A. Dzulkifli, “Stress Assessment While Listening to Quran Recitation,” *2014 Int. Conf. Comput. Assist. Syst. Heal.*, pp. 67–72, 2014.

[4] B. S. Zheng, M. Murugappan, S. Yaacob, and S. Murugappan, “Human Emotional Stress Analysis through Time Domain Electromyogram Features,” pp. 172–177, 2013.

[5] F. Bousefsaf, C. Maaoui, and A. Pruski, “Remote assessment of the Heart Rate Variability to detect mental stress,” *Proc. ICTs Improv. Patients Rehabil. Res. Tech.*, vol. 1, no. c, pp. 3–6, 2013.

[6] S. Sockeel, D. Schwartz, M. Pélégrini-Issac, and H. Benali, “Large-Scale Functional Networks Identified from Resting-State EEG Using Spatial ICA,” *PLoS One*, vol. 11, no. 1, 2016.

[7] U. Orhan, M. Hekim, and M. Ozer, “EEG signals classification using the K-means clustering and a multilayer perceptron neural network model,” *Expert Syst. Appl.*, vol. 38, no. 10, pp. 13475–13481, 2011.

[8] R. Khosrowabadi, A. Wahab, and K. K. Ang, “Affective computation on EEG correlates of emotion from musical and vocal stimuli From Musical and Vocal Stimuli,” in *Neural Networks, 2009. IJCNN 2009. International Joint Conference on*, 2009, pp. 1590–1594.

[9] R. S. S. A. Kadir, M. H. Ghazali, Z. H. Murat, M. N. Taib, H. A. Rahman, and S. A. M. Aris, “The Preliminary Study On The Effect Of Nasyid Music And Rock Music On Brainwave Signal Using EEG,” in *Engineering Education (ICEED), 2010 2nd International Congress on*, 2010, pp. 58–63.

[10] E.-H. Jang, B.-J. Park, S.-H. Kim, and J.-H. Sohn, “Emotion classification based on physiological signals induced by negative emotions: Discriminantion of negative emotions by machine learning algorithm,” *Proc. 2012 9th IEEE Int. Conf. Networking, Sens. Control*, pp. 283–288, Apr. 2012.

[11] P. van den Haak, R. van Lon, J. van der Meer, and L. Rothkrantz, “Stress assessment of car-drivers using EEG-analysis,” *Proc. 11th Int. Conf. Comput. Syst. Technol. Work. PhD Students Comput. Int. Conf. Comput. Syst. Technol. - CompSysTech ’10*, p. 473, 2010.

[12] F. Agrafioti, D. Hatzinakos, S. Member, and A. K. Anderson, “ECG Pattern Analysis for Emotion Detection,” *Affect. Comput. IEEE Trans.*, vol. 3, no. 1, pp. 102–115, 2012.

[13] R. W. Picard, “Affective computing: challenges,” *Int. J. Hum. Comput. Stud.*, vol. 59, no. 1–2, pp. 55–64, 2003.

[14] P. Ekman, “Facial expressions,” *Handb. Cogn. Emot.*, vol. 53, pp. 226–232, 1999.

[15] F. Hönig, A. Batliner, and E. Nöth, “Real-time Recognition of the Affective User State with Physiological Signals,” *Proc. Dr. Consort. (Affective Comput. Intell. Interact. Lisbon, Port. 12-*

14.09.2007), pp. 1–8, 2007.

[16] J. Anttonen and Surakka, “Emotions and heart rate while sitting on a chair,” *Proc. CHI 2005*, pp. 491–499, 2005.

[17] C. M. Jones and T. Troen, “Biometric valence and arousal recognition,” pp. 191–194, 2007.

[18] R. L. Mandryk, K. M. Inkpen, and T. W. Calvert, “Using psychophysiological techniques to measure user experience with entertainment technologies,” *Behav. Inf. Technol.*, vol. 25, no. 2, pp. 141–158, 2006.

[19] Z. I. Botev, J. F. Grotowski, and D. P. Kroese, “Kernel density estimation via diffusion,” *Ann. Stat.*, vol. 38, no. 5, pp. 2916–2957, 2010.

[20] D. Michie, D. J. Spiegelhalter, and C. C. Taylor, “Machine learning, neural and statistical classification,” *Citeseer*, 1994.

[21] G. Chanel, J. Kronegg, D. Grandjean, and T. Pun, “Peripheral Physiological Signals Emotion Assessment : Arousal Evaluation Using EEG ’ s and Peripheral Physiological Signals Computing Science Center , University of Geneva,” *Mulimedia Content Represent. Classif. Secur.*, 2006.