MOOD IDENTIFICATION IN PEOPLE USING ECG SIGNALS

Bhavya V [1], Dr. Thajudin Ahamed V I [2]

[1]PG holder, Dept. of Electronics and Communication Engineering, Wayanad, India
[2]Professor, Dept. of Electronics and Communication Engineering, Government Engineering College, Trissur, India

---***---

***Abstract** - Emotions may be situation depended and they have a great role in human life. Emotions depends on character and thoughts of human being. In many situation human can mask their emotions. The essential components of emotions are expressive, physiological and subjective constituent. They describes how we react or express, how our body react and how we feel the emotion. It is possible to recognize emotions using Electrocardiogram (ECG) signals. Since the heart rate depends upon the regular interplay of parasympathetic and sympathetic. Heart rate provide the information about autonomic flexibility. This project aims to recognize emotion in children using ECG signals. ECG signals are analyzed both in time and frequency domain. Here happy and fear is considered for analysis. T-test is done to find the correlation between the happy and fear. If the emotions are not correlated then P<0.01 and the obtained result is positive. Accuracy obtained is 87%. This is also applicable to people who can not express their emotions such as autistic patients, very aged people, new born child's etc.*

Keywords: Electrocardiogram(ECG), Heart rate variability(HRV), Heart rate(HR), autonomous nervous system (ANS), Support Vector Machines (SVM)

1. INTRODUCTION

Emotions consist of various components, including cognitive reactions, feelings, bodily changes, thoughts and behavior. Every basic function such as perception, decision making, learning etc., is deeply associated with emotions either directly or indirectly. Human communication would seem rather out of depth without an emotional expression. However, people who have difficulty with introspection and communication such as children with autism spectrum disorder cannot express their emotions. This makes difficulty to parents and care takers associated with these children to understand child's behavior.

The growth of technologies in emotion recognition is very fast. Several researchers have tried to identify emotions using various modalties like facial images, gestures, speech, physiological signals etc. The conventional emotional recognition techniques are based on the tone of human speeches, facial images but they lacks recognition accuracy. They are not universal and depend on external factors like culture, gender, age etc. But the physiological signals are involuntary in nature and as such as difficulty to mask. This motivates the development of emotion recognition using physiology signals such as ECG signals.

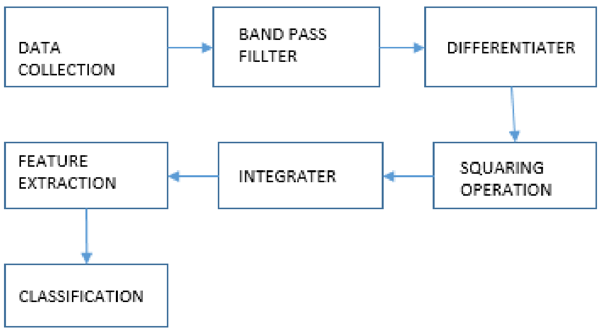
ECG signals indicates an activity of the autonomous nervous system (ANS) which will reflect the underlying true emotional state of a person. From ECG, R-R interval is used to calculate the heart rate and also the heart rate variability (HRV). HRV is the second derivative of ECG. The changes between consecutive inter-beat-intervals is described by HRV. The heart rate (HR) [12] is controlled by both parasympathetic and sympathetic branches of the ANS. Parasympathetic nervous system (PNS) activity increases HRV and decreases HR, whereas sympathetic nervous system (SNS) activity decreases HRV and increases HR [13].

Identifying the emotions using ECG signal is very helpful in applications such as computer-based training, human computer interaction, patients with autism and other intellectual disabilities etc. However, various methods introduced for emotion recognition but they lacks accuracy, and more robust methods need to be developed to identify the HR pattern associated with the emotional pattern.

2. LITERATURE REVIEW

Several methods are proposed for emotion recognition. Emotion is recognized by using facial expressions and speech signals are proposed by Ang et al., 2004; Bailenson et al., 2008; Kessous et al., 2009 [14]. Yet these modalities are voluntary in nature. Socially masked emotions, unexpressed emotions or minor emotional changes that cannot be perceived externally and also cannot be tracked using these modalities. Kim et al., 2004 proposed a different approach to recognize emotions by using physiological responses. As physiological signals represent the inherent activity of the autonomous nervous system, social masking does not have an impact in recognizing the true emotions felt by the person. This also gives a chance to identify minor emotional variations that cannot be identified on seeing or hearing a person (Rani and Sarkar, 2006). Several researchers provide various works (Andre et al., 2004; Kim et al., 2004; Korb et al., 2008) to identify emotional variations that are based on the bio signals such as electroencephalogram(EEG), electrocardiogram (ECG), skin temperature ,electromyogram, galvanic skin response, blood volume pulse and respiratory response etc. ECG signal has been introduced as a biometric characteristic signals for subject based emotion recognizer that takes the instantaneous variability of the signal from its homeostatic baseline. To detect the dynamically evolving emotion, pattern of ECG is introduced by Foteini et al. in 2012 using the empirical mode decomposition [11]. Classification features are calculated by using instantaneous frequency (Hilbert-Huang transform) and the local oscillation within every mode. Two experimental setups are presented for the elicitation of active arousal and passive arousal/valence. The results support the expectations for subject specificity, as well as demonstrating the feasibility of determining valence out of the ECG morphology (up to 89 percent for 44 subjects). In addition, passive and active arousal are differentiated by this work which is a not considered in the previous works. This gives a greater chances of ECG reactivity to emotion when the induction method is active for the subject. The six emotions such as happiness, fear, surprise, sadness, neutral and disgust which is studied by Jerritta et al.(2013) by using the ECG signals of subjects [10]. For accurate emotion recognition, Fourier spectral analysis and empirical mode decomposition (EMD) are combined. Wearable wristband is proposed by Niranjana et al.(2015) to acquire physiological signals. Support vector machine (SVM) is used as a classifier. This system will evaluate emotional states such as neutral, happy and involvement of children with autism [1]. The emotions are recognized based on the changes of body parameters on physiological basis such as the heart rate variability (HRV) and galvanic skin response (GSR). SVM classifies the different emotional states based on the extracted features of recorded physiological signals. Overall accuracy of 90% is obtained through this method. This project aims to recognize emotions only using ECG with high accuracy.

3. METHODS



Block Diagram

Methodology is as shown in Block diagram. First step is the data acquisition system. Data are collected from the children who are below 19 and above 5 years old. The raw ECG contain noises. ECG preprocessing steps are used to remove the noises. After the preprocessing, feature extraction is an important step to extract features from the signal. This extracted features will help to identify the emotion. Here time domain, frequency domain and non-linear method is considered for emotion recognition. And Support Vector Machine (SVM) classifier is used to classify the emotions either happy or sad.

3.1 ECG Preprocessing steps

The raw ECG data are prone to artefacts and noises that happen during the instrumentation, subject movement, electrode placement, power line, baseline wander or any other disturbances. Removal of artefacts and noise from the raw ECG are an important step before processing. ECG pre-processing deals with either the removal of unnecessary noise or with baseline correction.

3.1.1 Band pass Filter

The muscle noise, 60 Hz interference, T- wave interference and baseline wander noises are removed by the band pass filter. Approximately 5-15 Hz pass band is used to maximize the QRS energy. So combination of high pass and low pass filters (5-15 Hz) are used to get rid of these noises.

3.1.2 Differentiator

Differentiator is a standard method, used to find the high slopes. It differentiates the QRS complexes from other ECG waves. High gain is provided for the high frequency components which are arise from the high slopes of QRS complex and, low frequency components of P and T waves are suppressed by derivative procedure.

3.1.3 Squaring Function

After differentiation, the signal is squared by taking each position in a point by point manner. The equation of this operation is $y(nT) = [x(nT)]^2$. This operation makes all the result positive. It emphasizes the large differences that are obtained from QRS complex and suppress the small differences resulted from P and T waves. The high frequency components in the signal related to the QRS complex are further enhanced. This is a nonlinear amplification of the output of the derivative emphasizing the higher frequencies (that is predominantly the ECG frequencies).

3.1.4 Moving-Window Integration

Obtained the feature information and slope of the R wave by using the moving window integration. The number of samples which is expressed as N is important parameter of moving window. Generally, the width of the window size must be almost equal to the large possible QRS complex. If the window is too wide, the integration waveform will merge the QRS and T complexes together. If it is too narrow, some QRS complexes will produce several peaks in the integration waveform. This will cause difficulty in subsequent QRS detection processes. The width of the window can be determine empirically. Sample rate is 200 samples/s and the window must be 0.150 seconds length so as to get rid of noise.

3.2 Feature Extraction

Once the signals are preprocessed, it is necessary to extract features from the signal which can be used to detect the emotional content of the signal. Heart rate variability (HRV) features are extracted from R-R intervals. The R-R intervals are obtained from ECG waveforms, and is used to recognize emotions. HRV analysis is mainly focused on frequency and time domain analysis. However, cardiac activity is an integrated signal and it is influenced by ANS, various extrinsic factors and many other physiological mechanisms. In this work the Geometric analyses is also considered. More recent research reports that cardiac signals also contain non-linear components. Poincare plot is a non-linear as well as geometric analysis method.

3.2.1 Time domain HRV features

Time domain features are used to analyze HRV. All these calculates various aspects of statistical variability in the Inter-beat intervals (IBI) data series. IBIs is the time interval between two adjacent heart beats in ms. Time domain features such as mean RR, mean HR, std RR, std HR, pNN50, NN50, RMSSD are computed. Mean RR, Mean HR, std RR, std HR are the mean value of R-R intervals, mean value of HR, standard deviation of R-R intervals and standard deviation of HR respectively. In time domain measurements, root mean square of successive differences(RMSSD) is the most important parameter. This is calculated by determining the difference between adjacent IBIs before squaring and summing them, the average values and the square root is obtained. The RMSSD determines the high frequency beat-to-beat variations. Other parameters used to calculates beat-to-beat changes include the NN50. The NN50 is the number of neighboring IBIs that varies by greater than 50 ms, and the pNN50 is the proportion of beats varying by 50ms (NN50/ total number of IBIs). And these parameters are highly correlated with RMSSD.

3.2.2 Frequency domain HRV features

In Frequency domain analysis Welch's algorithm is carried out for spectral analysis. Welch algorithm estimates the power spectrum by using an averaging modified periodogram. The power spectrum of the HRV signal is divided into 3 bands namely very low frequency-VLF (0 to 0.04 Hz), low frequency-LF (0.04 to 0.15 Hz) and high frequency-HF (0.15 to 0.5 Hz) where LF and HF bands are related to sympathetic and parasympathetic activities. Extracted features from these frequency bands are peak LF, peak HF, Power in percentage etc. The power spectrum of R-R intervals for happy and fear emotions are obtained. It is observed that the relative powers across different frequency bands are different for two different emotions. Therefore, the features extracted from these bands will serve as a good discrimination factor to classify different emotions.

3.2.3 Geometric analysis

Geometric calculates metamorphose sequences of IBIs into geometrical forms and the assessment of HRV is extracted from these forms. The most prominent geometrical measures are poincare plot and the TINN index. TINN index is the baseline width of then minimum square difference triangular interpolation of the highest peak of the histogram of all IBIs.

Poincare Plot Geometry

Poincare plot is named after Henri Poincare. It is used to compute a self-similarity in processes. In Cartesian plane, time series is geometrically represented by using Poincare plot. Poincare plot is a non-linear method used to describe the attributes of R-R interval variations. In this graph each of the R-R interval is plotted against the next interval. Representation of time series on Cartesian plane or phase space is constructed by plotting consecutive points. Poincare plot is a map of dots in an XY-diagram. Duration of an IBI is indicated by dots and it is plotted against the previous IBI duration. The length of this plot corresponds to the level of long term variability, while the width of the plot indicates the level of short term variability. Two basic descriptors of the plot are SD1 and SD2 that is shown in next section (Fig.4.6 and 4.10). The line of identity is the 450 imaginary diagonal line on the Poincare plot. The points including on the imaginary line obeys the property Xn =Xn+1. Instantaneous short-term HRV is represented by SD1. The plot is then rotated 450 counter clockwise and again the SD of the plot is calculated around the horizontal axis for finding the SD of SD2 which is the long term variability. SD1 calculates the distribution of points which is perpendicular to the identity line. The SD2 calculates the distribution along the identity line. Basically, SD1 and SD2 of Poincare plot is directly related to the basic statistical measures, time series standard deviation(SDX), and standard deviation of the consecutive difference of time series (SDSD). Quantitative Poincare calculation have been found to give the useful information.

3.3 Classification

Support Vector Machines (SVM) is a hyper plane classifier S(x) =< w; b > +b is commonly used to solve two class problems. More complex pattern distribution can be solved by using the supervised learning model such as SVM. It shows higher performance. SVM is computational machine learning systems that use a hypothesis space of linear functions in a high dimensional feature space to perform supervised classification. Feature vector data points are constructed by the SVM through the construction of discriminant function. The distance between the distinct function and the nearest training set is simultaneously maximized. It can predict the test set which is either belongs to class 1 or class 2. The capability is verified by divides the input samples into test sets and training sets. This will be used in k-fold cross validation techniques. This strategy eliminates the need to test on unknown physiological signal samples whose labels (targets) may be uncertain. In this work, Weka software is used for classification. Data mining tasks are performed by using a group of machine learning algorithms. The learning classifier is retrained and retested after the individual signal removal by using the same cross validation scheme. SVM classifier has given the highest classification accuracy.

4. RESULTS AND DISCUSSION

This section presents some of the results obtained by applying the methods which are described above. First of all, only two emotions are recognized.

Table 4.1 Result of time domain analysis of HR data

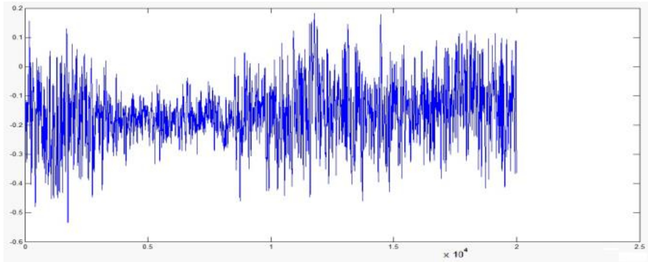
Indices	Happy	Fear
TINN	145	180
SD1	796.73	45.6
SD2	0.032	0.044
Std HR(per min)	407.77	375.05
RMSSD(ms)	9.9	15.5
NN50(count)	0	1
pNN50(percentage)	0	17.6

Table 4.2 Result of frequency domain analysis of HR data

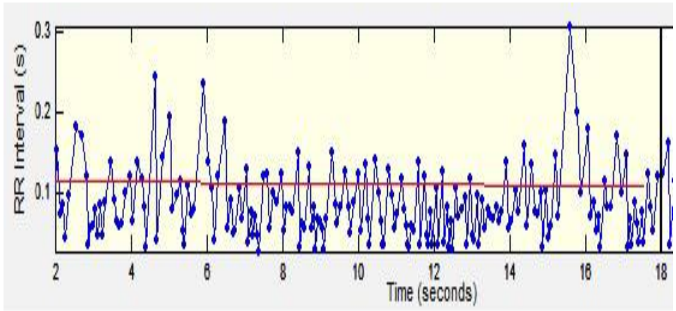
Indices	Happy	Fear
Peak LF	0.1152	0.0703
Peak HF	0.3027	0.2090
VLF Power(percentage)	18.5	0
LF Power(percentage)	49.5	54.8
HF Power(percentage	32	45.2

Table 4.3: Result of Geometric analysis

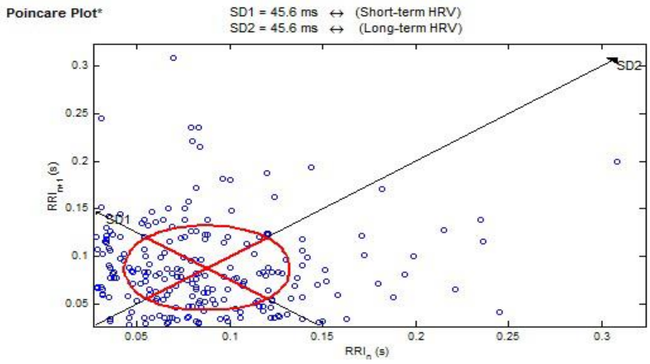
Indices	Happy	Fear
TINN	145	180
SD1	35.3	45.6
SD2	28.1	46.9



4.4 Raw ECG (Fear)



4.5 R-R interval (Fear)



4.6 Poincare plot (Fear)

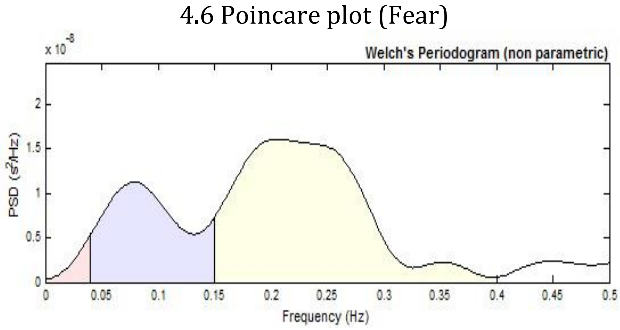


Figure 4.7: Welch's Periodogram (Fear)

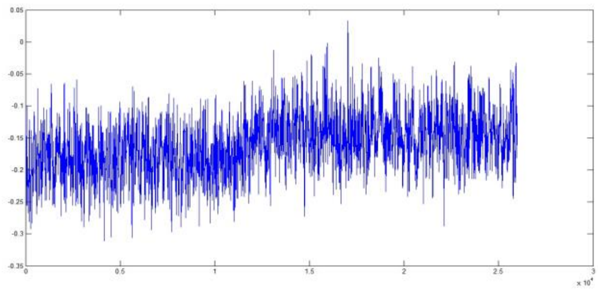
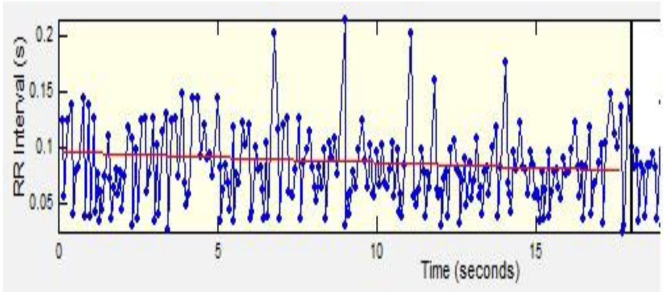
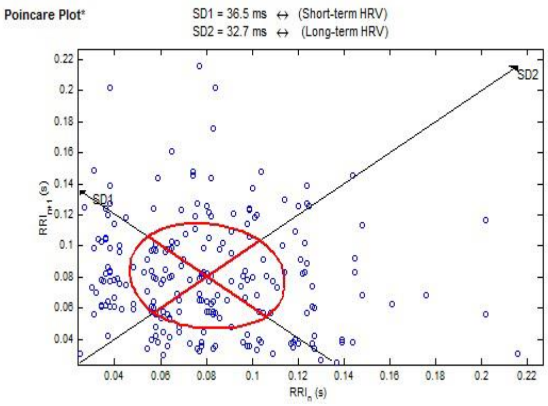


Figure 4.8 Raw ECG of happy



4.9 R-R interval (Happy)



4.10 Poincare plot(Happy)

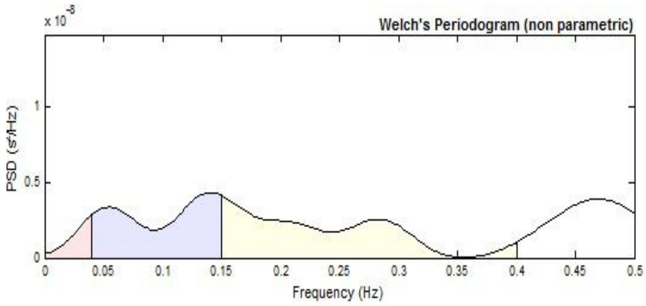


Figure 4.11: Welch's Periodogram(Happy)

Figure 4.4 and 4.8 shows the raw ECG of happy and fear. We can not differentiate the R-R interval plot of happy and fear (Fig 4.5 and 4.9). The accuracy of frequency domain, Time domain and Geometric analysis depends on the data length. Poincare plot is a nonlinear method that can help to analyze signals qualitatively and quantitatively. It reflects the variability of data. From figure 4.6, SD1 is 45.6 and from figure 4.10, SD1 is 38.5 ms. The emotions are time depended and they ends within minutes or seconds. Thus obtaining high quality data for emotion analysis is difficult. The accuracy obtained in this work is better than that of the works by previous researchers.

5. CONCLUSION AND FUTURE SCOPE

Emotion Recognition Using ECG signals is an efficient method to determine the emotional states of Children. One of the benefits of detecting emotions using ECG signals is that these are involuntary reactions of the body, and as such are very difficult to mask. In this project it is very important to collect meaningful data. Several preprocessing steps are used to remove the noise from the raw ECG data and R-R intervals are extracted for the computation of the HRV. Emotion recognition is based on the time domain and frequency features of R-R interval, and poincare plot is also considered as non-linear method. Higher accuracy is achieved through this methods. This system will be helpful to very aged people, new born, patients with Autism etc., who will not be able to express their emotions explicitly. Suggestion for future scope is that to develop a new method based on non-linear analysis(Hurst) to emotion recognition using ECG signals. Another one is that the ECG and electroencephalogram (EEG) signals can be considered together for highly accurate emotion recognition.

Acknowledgement

I am very thankful to Prof. Sindhu N, Asst. Prof. in Electronics and communication Engineering Government Engineering College, Trissur, for her valuable support.

REFERENCES

[1] Niranjana Krupa1 , Karthik Anantharam, Manoj Sanker, Sameer Datta ,and John Vijay Sagar, "Recognition of emotions in autistic children using physiological signals", Springer Journal March 2016.

[2] Hany Ferdinando, Tapio Seppanen,and Esko Alasaarela "Comparing Features from ECG Pattern and HRV Analysis for Emotion Recognition System", Ministry of Higher Education and Research,Indonesia 2013.

[3] Jiapu Pan and Willis J. Tompkins, "A Real-Time QRS Detection Algorithm", IEEE transactions on Biomedical Engineering, Vol. Bme-32, NO. 3, March 1985.

[4]S.Karpagachelvi, Dr. M.Arthanari,and M.Sivakumar_ International Journal of Computer Science and Information "ECG Feature Extraction Techniques - A Survey Approach", International journel of computer science and information security vol.8 ,2010

[5] Teo Kah Ming "The study of ECG in relation to human emotions", Neurosensors Laboratory, Department of Mechanical Engineering.

[6] Raj Rakshit, V. Ramu Reddy,and Parijat Deshpande, "Emotion Detection and Recognition using HRV Features Derived from Photoplethysmogram Signals", ERM4CT'16, November 2016.

[7] Shalini Sahay, A.K.Wadhwani,and Sulochana Wadhwani, "A Survey Approach on ECG Feature Extraction Techniques", International Journal of Computer Applications (0975-8887) Volume 120 , No.11, June 2015.

[8] Han-Wen Guo ,Yu-Shun Huang,Chien-Hung Lin, Jen-Chien Chien and Jiann-Shing Shieh, "Heart Rate Variability Signal Features for Emotion Recognition by using Principal Component Analysis and Support Vectors Machine", IEEE

16th International Conference on Bioinformatics and Bioengineering 2016.

[9] Kwang-Ho Choi, Junbeom Kim, O. Sang Kwon, Min Ji Kim, Yeon Hee Ryu and Ji-Eun Park, "Is heart rate variability (HRV) an adequate tool for evaluating human emotions? A focus on the use of the International Aeffective Picture System (IAPS)", Psychiatry Research 251 (2017).

[10] Jerritta Selvaraj, Murugappan , Khairunizam Wan and Sazali Yaacob, "Classi_ca- tion of emotional states from electrocardiogram signals: a non-linear approach based on hurst", BioMedical Engineering Online 2013.

[11] Foteini Agra_oti, Dimitrios Hatzinakos, and Adam K. Anderson, "ECG Pattern Analysis for Emotion Detection", IEEE Transactions on a_ective computing, vol. 3, NO. 1, January-March 2012.

[12] Silvia De Nadai, Francesco Parodi, Mauro Benza, Anita Trotta, Enrico Zero, Luca Zero, Roberto Sacile, "Enhancing safety of transport by road by on-line monitoring of driver emotions", Department of Informatics, Bioengineering, Robotics and System Engineering(DIBRIS) Italy .

[13] Mika P. Tarvainen, Jukka Lipponen, Juha-Pekka Niskanen, and Perttu O. Rantaaho, "Kubios HRV (ver. 3.0)", 2017.