International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 08 | Aug 2020 www.irjet.net p-ISSN: 2395-0072
National Conference on Recent Advancements in Communication, Electronics and Signal Processing-RACES'20
Organised by: Department of ECE, Velammal Engineering College, Chennai-66

CLASSIFICATION OF EMOTIONAL STATES USING ECG SIGNALS AND SVM

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Abstract: Emotion identification improves communication between humans and machines. Thus Human-Computer Interface that is engaged for various real-time uses will be additionally useful if emotions are merged in the scheme. Generally, it is a complex procedure to decide and group emotional situations. Emotional variations in human beings take significant influence on human fitness, hence defining emotions with high precision is essential. The core aim of this effort is to increase the efficiency of emotional state classification. Hence, this effort, groups emotion into two as favourable emotions and unfavourable emotions. The classification efficiency can be improved with accurate input data, appropriate features and efficient classification algorithms. The ECG data used for analysis are taken from physionet ECG database, and a capable Support Vector Machine (SVM) classifier is utilized. Classification efficiency is further improved by selecting appropriate ECG signal features. Thus from the analysis, it is observed that two time-domain characteristics and three frequency domain characteristics, thus a total of 5 features, can competently group the two emotional states as favourable emotions and unfavourable emotions.

Keywords: emotional state, ECG, SVM.

Introduction

The interface between machine and humans is applied in several real-time industrial applications, telemedicine, automation applications etc. These applications will be practical only if information transfer is without error. There is an impact of emotions on cognitive development of brain-like such as knowledge, retention, etc. The unfavourable emotions like anger, stress affects human fitness and is responsible for various disease caused by human beings. Hence emotions influence the physiological signals, expressions on the face, speech etc. [1]. Agrafoti [2] proved in his work that ECG signals are better in identifying the emotional state compared to other methodologies.

The Parasympathetic Nervous System (PNS) and Sympathetic Nervous System (SNS) produces various grades of arousal for dissimilar kinds of emotions, thus considerably performs as a practical sign for dissimilar groups of emotions [3]. The emotion identification system consists of three major blocks, data acquisition, feature extraction and classification. The data for this work is obtained from physionet database. Various categories of emotions are grouped into two categories, positive and negative emotions, and the classification method used is Support Vector Machine, that is proved to be an efficient classifier for emotion detection [4]. The foremost aim of this work is to determine the effective HRV characteristics, to enhance the precision of the emotion classification scheme.

Methodology

Figure 1 displays the basic block diagram of the emotion categoriation scheme.

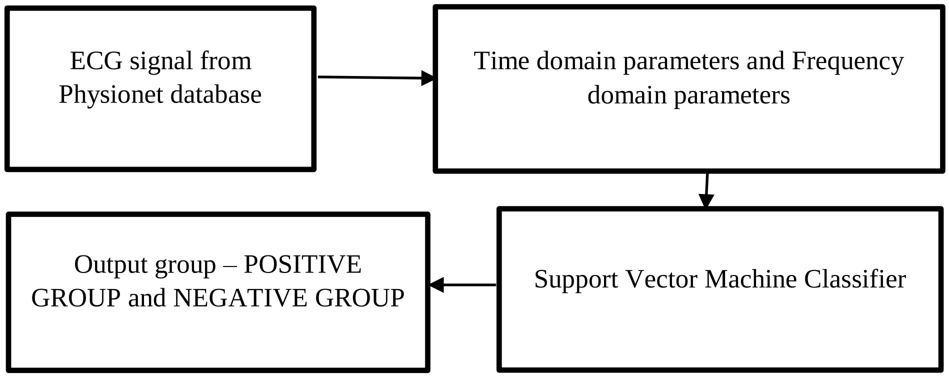

Figure 1: Block Diagram of Emotion Categorization System

Fifty-six dataset are considered from physionet database, amongst that 75% of data is utilized for the training dataset and 25% dataset is utilized for testing. Hence amongst 56 dataset considered from the database, 42 data are considered for training and 14 utilized as testing dataset. Heart rate is described as the quantity of heartbeats per minute. There is a change in time pauses between heartbeats called Interbeat Intervals (IBIs), defined as Heart Rate Variability (HRV). The oscillations of the heart are complicated, and it is always varying that adjusts to the variations in physical and psychological variations. Thus HRV is described as the variations in the time pauses among the subsequent heartbeats. The time parameters of HRV, quantify the quantity of variability in measurements of the time epoch among consecutive heartbeats. The frequency characteristics explain the spreading of absolute or relative power into four groups of frequency [5].

SDNN is defined as the standard deviation of the Interbeat Intervals of regular sinus beats and is calculated in ms. The activity of both SNS and PNS contributes to SDNN that is associated with the amount of ULF, VLF, LF power and also with total power. SDRR is the standard deviation of Interbeat Intervals for every sinus beats that also comprises abnormal beats. The abnormality may also be due to the dysfunction of the heart [6]. The value of NN50 is specified by the amount of succeeding NN intervals that varies by additional 50ms and involves a 2 min period. pNN50 is the proportion of nearby NN pauses that vary from each other by additional 50ms and also involves a 2-min epoch. RMSSD is described as the root mean square of sequential dissimilarities among the regular heartbeats. NN50 and pNN50 are determined by calculating the differences between successive NN intervals [7].

The Fast Fourier Transformation (FFT) or Autoregressive (AR) modeling is used to split the HRV frequency characteristics into its constituents ULF, VLF, LF and HF. The Ultra-low-frequency (ULF) group is in the series of less than 0.003Hz and is extremely interrelated with the SDNN time-domain index. The VLF group is defined in the frequency series of 0.0033Hz to 0.04Hz. The LF band is in the series of 0.04 to 0.15 Hz. The HF group series between 0.15 Hz to 0.40 Hz [8].

SVM is good for categorization of the input data when the data is not equally distributed. The selection of kernel helps to enhance the grouping efficiency of SVM since there is a choice in selecting the threshold and the value it can assign may be non-linear. It is capable to produce unique solution. The classification is performed by evolving a hyperplane which isolates the data into two groups. This type is a supervised learning category which works in two phases training and testing. The basic principle of operation is to make the most of the space among the support vectors by describing appropriate kernel function [9].

Results and Discussion

56 dataset are considered for analyzing the outcome. 42 dataset is employed for training, and 14 dataset is utilized for testing. The two groups of emotional states are favourable emotions and unfavourable emotions. Sadness, Angry and fear are considered to be unfavourable emotional groups while happiness, relax, excitement are classified under favourable emotional group. The HRV features are calculated and grouped into two groups of characteristics, time domain and frequency domain features. In the time domain, seven features, MeanRR, SDNN, MeanHR, NN50, PNN50, STDHR and RMSSD, are measured, and in the frequency domain, four features VLF, LF, HF and LF/HF are considered [5]. Therefore a sum of 11 characteristics is considered for investigation. The study is accomplished for diverse groupings and also because of the dissimilar set of feature grouping in both time and frequency characteristics. In Table 1, the complete analysis for a diverse mixture of the frequency domain, time-domain features and grouping of both characteristics are listed. By associating the competence attained, it can be perceived that great efficiency is acquired for 11 features and a minimum for three features. From the outputs achieved that are tabulatedl in the table, it can be perceived that the characteristics with a grouping of 5 features, tow from time-domain meanHR, SDNN, and three features from frequency domain LF, HF, LF/HF gives high effectiveness. Therefore these five parameters can be utilized to achieve a great effective emotion grouping system.

Table 1: Classification efficiency of different combinations of time domain and frequency domain features

No. of Features	Emotional State	Time Domain characteristics	Frequency Domain characteristics	Time and Frequency domain characteristics together
9	Characteristics	MeanRR, SDNN, MeanHR, NN50, PNN50, STDHR, RMSSD	VLF, LF	MeanRR, SDNN, MeanHR, NN50, PNN50, STDHR, RMSSD, VLF, HF
	unfavourable	100	75	100
	favourable	100	75	100
	Average	**100**	**75**	**100**
7	Characteristics	MeanRR, SDNN, MeanHR, STDHR	VLF,LF,HF	MeanRR, SDNN, MeanHR, STDHR, VLF, LF, HF
	unfavourable	0	75	100
	favourable	100	100	100
	Average	**50**	**87.5**	**100**
5	Characteristics	MeanHR, SDNN	LF, HF, LF/HF	MeanHR, SDNN, LF, HF, LF/HF
	unfavourable	75	100	100
	favourable	100	100	100
	Average	**87.5**	**100**	**100**
3	Characteristics	NN50, PNN50	VLF	NN50, PNN50, VLF
	unfavourable	75	75	100
	favourable	25	50	50
	Average	**50**	**62.5**	**75**

Conclusion

Emotions are accountable for various physical and psychological illnesses when human beings face challenging circumstances. Thus in this work, suitable characteristics are recognized for competent grouping. Physionet dataset is considered, and SVM classification is utilized. The grouping of different time domain and frequency domain features are considered with 9, 7, 5, 3 features with separate time domain and frequency analysis and a combination of both. The detailed analysis demonstrates that five features are adequate for efficient emotion classification.

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