GR106

Emotion Recognition Using Wireless Signals

Abstract

Emotion Recognition plays an important role in understanding human behavior. It finds its utility in various domains such as healthcare, automobile industries, understanding social interactions, fraud detection, and many more. Analyzing a person's emotions in a controlled environment with various devices has been challenging since it adds to human anxiety, which manipulates the readings. This presents a need to devise ways to recognize and study emotions in a wireless manner. We devised a system that recognizes the emotions using Heart Rate Variability (HRV) of the subjects which is estimated from their videos using Remotephotoplethysmography(rPPG). Our emotion recognizer has 93.27% accuracy.

Motivation

1. Facial expression analysis or eye pupil movement analysis for emotion recognition could be delusive
2. How a person thinks and how he feels directly impacts his sympathetic and parasympathetic nervous system, especially the Heart rate. Physiological signals give accurate impression of human emotions.
3. Using wearable or wired devices for collecting physiological signals in human consciousness contaminate them.
4. These factors lead to need of recognizing emotions in wireless manner by analyzing physiological signals.

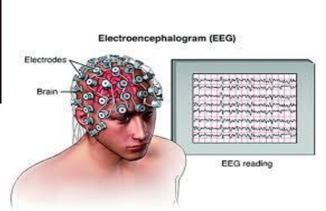
Background

Previous work is done to recognize emotions using,

Facial expressions

Eye Fixation Data

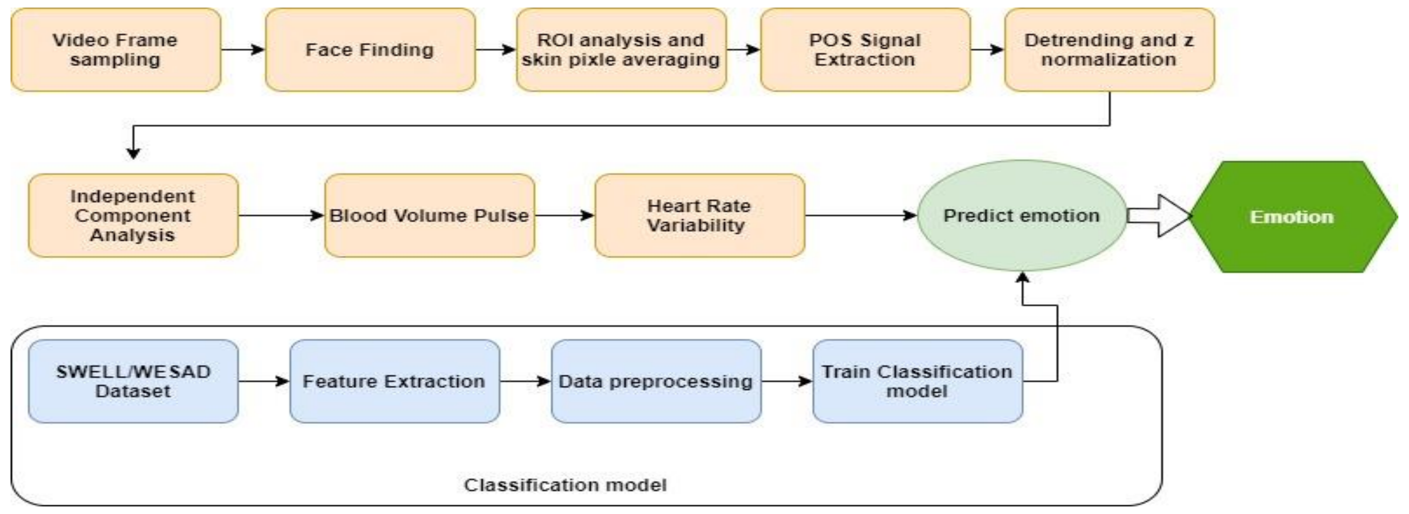
ECG



EEG

rPPG was also used to estimate Pulse rate variability (PRV) which helped in recognizing emotions

Methodology



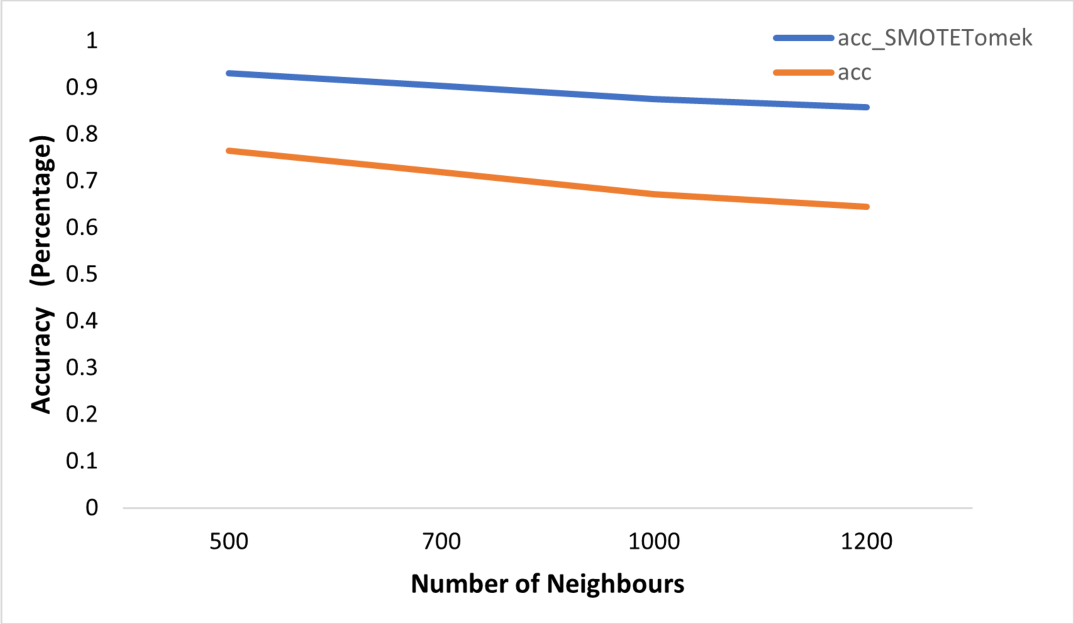
Datasets

1. SWELL and WESAD datasets are HRV datasets with corresponding emotions of subjects. They are used to train the model and test the accuracy of emotion recognizer. Testing is done using these datasets considering the HRV signals are most accurate.

2. RAVDEES dataset is a video dataset of 24 subjects and their corresponding emotions. Videos are processed to obtained HRV signals using existing rPPG system.

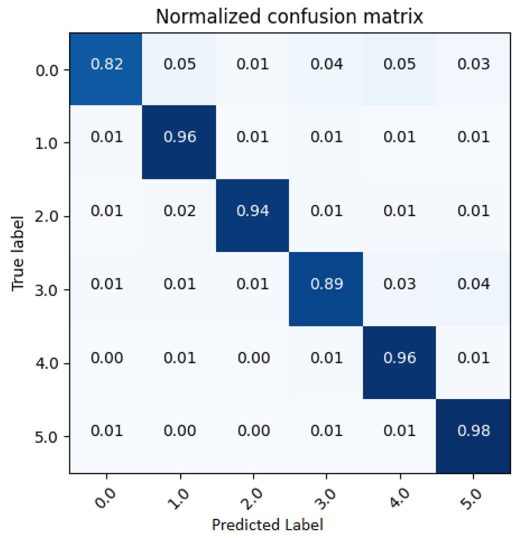
Results

Selection of value of nearest neighbors by finding it corresponding to lowest error rate. For SWELL-WESAD dataset, we found KNN model with K=500 has lowest error rate.



Accuracy of KNN model for K =500 has highest accuracy and later decreases gradually.

Confusion matrix showing the results of predicted emotions corresponding to true emotions.



These values are used to find how better the model has performed. We calculate the accuracy, F1-score, recall, precision using confusion matrix.

Each class represents an emotion:

Class 0 : no stress
Class 1 : Interrupted
Class 2 : Under Pressure
Class 3: baseline
Class 4: amusement
Class 5: stressed

Stressed people are identified more accurately by our model 98% of times!!

State of art/ Proposed	Physiological signals	Model	Accuracy
2019, Sabour et. Al.	rPPG + PRV	SVM	59.79%
Proposed (Swell Wesad)	rPPG + HRV	KNN classifier	93.27%
Proposed (RAVDEES)	Existing rPPG + HRV	KNN classifier	37.23%

Conclusions

1. HRV signals are more affected by Emotions than PRV signals
2. This technique could be used in various fields to find emotions even without the subject knowing about their emotions being recognized.
3. 93.27% accuracy is obtained by emotion recognizer using SWELL WESAD dataset

Future work

Our system requires subject to look into camera to capture HRV properly and then process to get accurate emotions. As part of future work, we plan to increase accuracy of emotion recognizer using HRV of subjects who are far away from camera and not looking at it.

Acknowledgments

We would like to thank my Machine learning Professor, Dr. Mohammed Aledhari for guidance and motivation provided to us time to time. I would like to thank Department of Computer Science and Software Engineering to provide me this opportunity.

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