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HUMAN EMOTION DETECTION USING SOFT COMPUTING METHODS

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Abstract: Emotion recognition is the process of understanding what type of affect (emotion) a person is expressing. The development of efficient and robust algorithms for automated recognition of human affect is a major challenge for the field of affective computing and may have great implications on the way people interact with computing devices. In this project we have used DREAMER dataset for emotion recognition using EEG and ECG signals. The artifacts and noise present in the signals were removed using pre- processing techniques like FIR filters using hamming window for EEG signals. The EEG signals were separated into theta(4-8Hz), alpha(8-13Hz) and beta(13-20Hz) frequency bands. PSD of each EEG bands are estimated using Welch's method. All the features were concatenated and stored in CSV file. ECG features like mean, median, standard deviation, min, max, and range from each part of the PQRST complexes, difference between consecutive RR intervals (RMSSD), PSD for Low Frequency (LF), PSD for High Frequency (HF), LF to HF ratio, total power using NeuroKit2 tool Box was used for ECG signals.

Index Terms – Hamming window, PQRST complexes, Welch's method, Power spectral density, pre-processing, Feature Extraction and reduction.

1. Introduction

Humans' works with **different machines for the rest of his life. Similarly, emotions are important and inevitable in everyone's life. More interaction** between equipment and people are the most obvious and obvious events in which a machine knows only when a specific command is sent, such as pressing a button. So, the interaction between machines and humans is independent and less intelligent. Scientists have found evidence that emotional abilities are fundamental part of wisdom. Reeves and Nass [1] have shown that replacing one of people in Human- Human Interaction (HHI) machine following the same basic rules of HHI. Therefore, it has become necessary to come up with a system in which it can detect the emotions of the person it is working with, system can mimic assets of the open communication that exists in human interaction. Active computer in research and development of a system that can detect and function effectively human influences or emotions. Picard is a pioneer working in the field of Affective Computing states that "Emotions play an important role in making informed decisions, comprehension, learning and various other mental functions". Therefore, the system development mentioned above will open the gate to purpose, strong, natural, and reliable interaction between machines and humans.

In this paper we use Electroencephalography (EEG) as well as Electrocardiogram (ECG) for effective recognition of emotions with the help of DREAMER dataset. Different strategies and steps are needed to separate emotions in EEG and ECG Signals. These steps include Signal Recording, pre- processing of recorded signals to extract artifacts from them, extracting the most appropriate element from the processed signals, formatting the database and testing it using a machine learning tool.
Brain activity produces a variety of signals such as electrical and magnetic signals [3]. This work can be recorded using a variety of methods, which are often classified as offensive and non-invasive. In invasive procedures a surgical intervention is performed to insert a device into the brain while in non-invasive ways no such intervention is performed. Among the various unconventional methods, Electroencephalography is one of the most widely used methods to record brain symptoms [3]. EEG is considered to be a straightforward and non-invasive method to record brain electrical activity, represented as fluctuations in electrical energy induced by current flow within brain neurons [8]. EEG waves that can be represented as a signal are later recorded by electrodes placed on the skin over the brain.

The heart is one of the most critical organs in the human body, and electrocardiography (ECG) is considered to be one of the most powerful diagnostic tools in medicine that is routinely used for the assessment of the functionality of the heart. ECG being a physiological signal is used as the conventional method for non-invasive interpretation of the electrical activity of the heart in real time. But is usefulness not only in analysing the heart's activity it can be also used for emotion recognition. ECG play a vital role in developing portable, nonintrusive, reliable, and computationally efficient emotion recognition systems. Understanding human emotions using physiological signals is one of the active research areas on developing intelligent human–machine interface (HMI) systems and Cyber Physical Systems with Human in the Loop. 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. The electrical cardiac signals are recorded by an external device, by attaching electrodes to the outer surface of the skin of the patient's thorax.

Data set

The dataset used is DREAMER, a multi-modal database consisting of electroencephalogram (EEG) and electrocardiogram (ECG) signals recorded during affect elicitation by means of audio-visual stimuli. Signals from 23 participants were recorded along with the participants' self-assessment of their affective state after each stimuli, in terms of valence, arousal, and dominance. All the signals were captured using portable, wearable, wireless, low-cost and off-the-shelf equipment that has the potential to allow the use of affective computing methods in everyday applications. The Emotiv EPOC wireless EEG headset was used for EEG and the Shimmer2 ECG sensor for ECG. The database is made publicly available in order to allow researchers to achieve a more thorough evaluation of the suitability of these capturing devices for affect recognition applications. The DREAMER database contains the participant ratings and physiological recordings of an experiment where 23 volunteers watched 18 film clips selected and evaluated by Gabert-Quillen et al. [1]. EEG and ECG signals were recorded and each participant rated their emotion by reporting the felt arousal, valence and dominance on five point scales.

2. Method

For classification of Emotion, the obtained EEG and ECG signals must undergo different set of pre- processing stages respectively. The flow diagram for the pre-processing is as shown in the block diagram

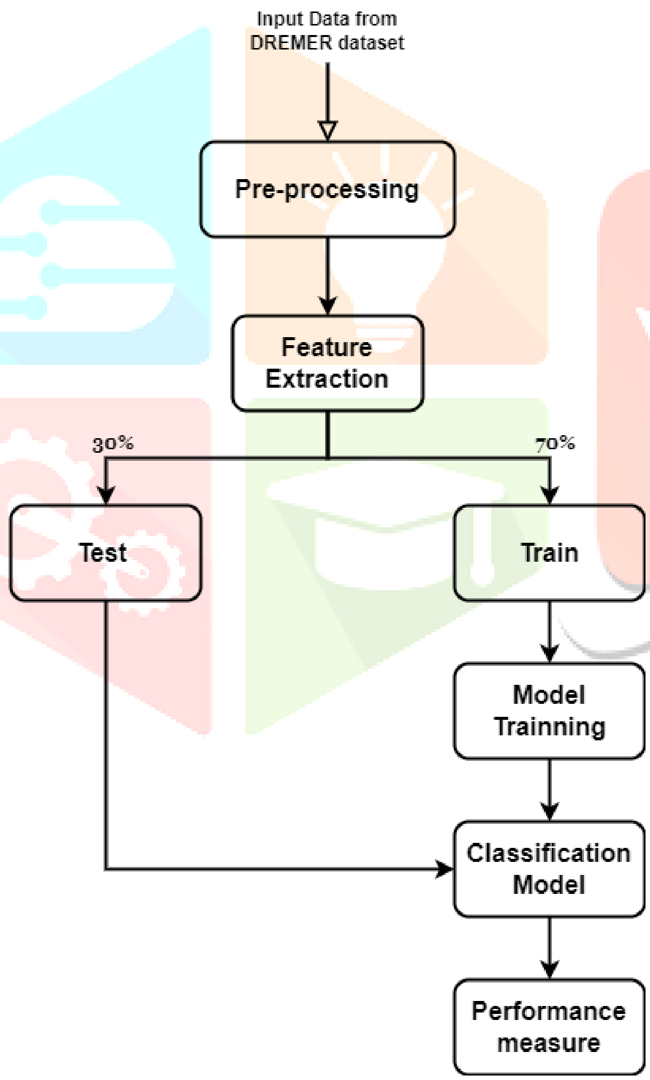


Fig 1: Block diagram

2.1 Pre-processing

For EEG, in this process we are removing noise and artifacts present in the signal using FIR filters using hamming window. The signals from cardiac activity, eye movement and muscle activity are also captured by EEG device which will downgrade the quality of data. Eye blinking signals are dominant below 4Hz and muscle movement artifacts are above 30Hz. So, we do emotion recognition task in the range 4-30Hz. The frequency of brain signals ranges from 4-30Hz.

For ECG, the raw ECG data were separated from other peripheral signals for the study to perform analysis on heart signals only. The databases were stored in .mat file. So, before starting out, the ECG signals were exported into .csv file and managed according to subject dependency. ECG signals are less susceptible to interferences due to their higher voltage amplitudes and thus require no further processing.

2.2 Feature extraction

Power spectral density (PSD) of EEG signals in different bands are correlated with affective state of human. Higher frequency components of EEG signals carry more important information regarding positive emotions compared to negative ones. After the pre-processing step, the captured EEG signals are separated into theta(4-8Hz), alpha(8-18Hz), and beta(13-20Hz) frequency bands. Welch's overlapped segment averaging estimator is then used to estimate the PSD of each EEG bands, using a 256 samples window with an overlap of 128 samples. The logarithms of PSD from each band are extracted from signals of each 14 electrodes in order to be used as features. (3*14) = 42 features, All the features are concatenated and stored in CSV file.

For ECG signals, the mean, median, standard deviation, min, max, and range from each part of the PQRST complexes, difference between consecutive RR intervals (RMSSD), PSD for Low Frequency (LF), PSD for High Frequency (HF), LF to HFratio, total power were features extracted. The Pan- Tompkins QRS detection algorithm is first used in order to detect the locations of QRS complexes within the ECG signal and accurately detect R- peaks. Statistical features, such as the mean, median, standard deviation, min, max, and range, are extracted from each part of the PQRST complexes of the ECG data using the Augsburg Bio signal Toolbox (AuBT). Then, the following HRV features are extracted using Vidaurre et al.'s BioSig toolbox [43] which provides methods for biomedical signal processing: difference between consecutive RR intervals (Root Mean Square of the Successive Differences–RMSSD), power spectral density (PSD) for Low Frequency (LF), PSD for High Frequency (HF), the ratio of LF to HF, and the total power. A total of 71 features are computed from the captured ECG signal and are concatenated into the final feature vector FECG. Heart rate variability may decrease with fear, sadness and happiness, while when a stimuli induces pleasantness, then the peak heart rate response may increase. Taking into consideration the effect of the emotional state on ECG-based features, features derived from the HR (Heart Rate) and HRV (Heart Rate Variation) of the recorded ECG signals are computed. Stress can be detected by HRV while HR is used to detect emotions related to negative and positive.

2.3 Classification

The dataset is split into test data (30%) and train data (70%). The train data is used to train the model and test data is used to test the predictions of the machine learning model. Supervised classification algorithms are used for emotion recognition using the features extracted. Three different binary classification schemes

1. Classification between low/high arousal. (Low arousal-calm, high arousal-excited)
2. Classification between low/high valence. (Low valence-pleasant, high valence-pleasant)
3. Classification between low/high dominance. (Low dominance-without control, high dominance-empowered).

Accuracy is calculated to find the performance of different classification algorithms.

Proposed 3D Emotional model incorporates Valence Arousal-Dominance versus Valence-Arousal space Russell's model of 2D Emotional model. The eight clusters gives rise to 8 different emotional states namely relaxed, peaceful, bored, disgust, nervous, sad, surprise and excited. Thus, each participant is given an emotional status label indicating the overall emotional state of the participant over time to do research. Fig 2 depicts the 3D model for Valence Arousal-Dominance.

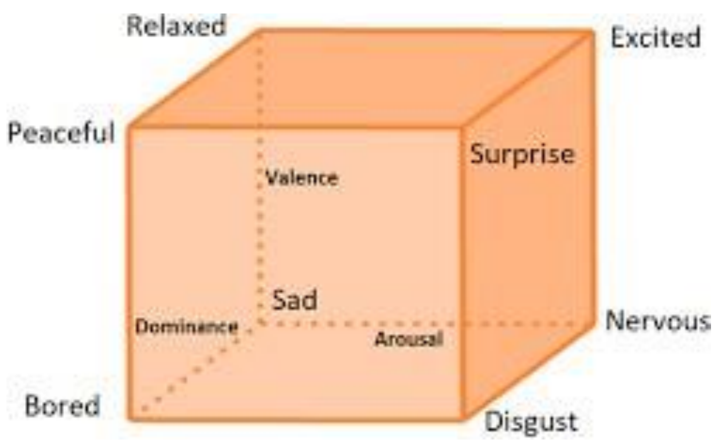
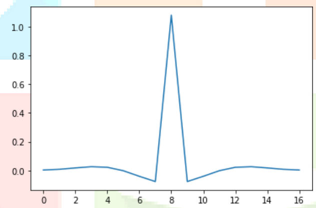


Fig 1: 3-D representation of Valence-Arousal- Dominance

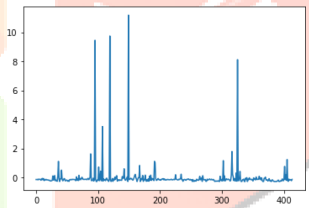
Clusters	Emotional State
HV LA HD	Relaxed
HV LA LD	Peaceful
LV LA LD	Bored
LV HA LD	Disgust
LV HA HD	Nervous
LV LA HD	Sad
HV HA LD	Suprise
HV HA HD	Excited

High valence (HV), Low valence (LV), Low arousal (LA), High arousal (HA), High dominance (HD), Low dominance (LD).

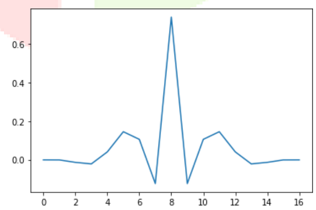
3. Results and Discussions



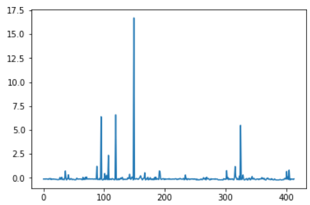
(a) Alpha1 after FIR Hamming



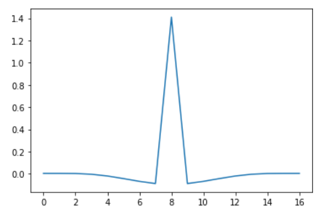
(b) PSD of Alpha1



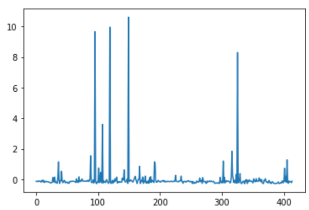
(c) Beta1 after FIR Hamming



(d) PSD of beta1



(e) Theta1 after FIR Hamming



(f) PSD of Theta1

Figure: Results Table

Table: Accuracy found for different Machine learning methods

	Valence	Arousal	Dominance
SVM	56.8%	49.6%	47.2%
LR	54.4%	57.6%	57.6%
NN	56.8%	57.6%	60.08%

(a) For EEG

	Valence	Arousal	Dominance
SVM	56.8%	49.6%	47.2%
LR	55.2%	53.6%	56.8%
NN	54.4%	56.8%	56.8%

(b) For ECG

	Valence	Arousal	Dominance
SVM	56.8%	49.6%	47.2%
LR	54.4%	57.6%	57.6%
NN	56.8%	57.6%	60.08%

(c) For EEG+ECG

4. Conclusion

In this project DREAMER dataset was used which consists of 23 participants EEG and ECG data collected using electrodes. Artifacts and noise in the signal were removed using FIR filters using hamming window. Welch's method was used for PSD estimation of EEG signals. The extracted features were used for classification. Neurokit toolbox was used for extracting ECG features like mean, median, standard deviation, min, max, and range from each part of the PQRST complexes, difference between consecutive RR intervals (RMSSD), PSD for Low Frequency (LF), PSD for High Frequency (HF), LF to HF ratio, total power, HR (Heart Rate) and HRV (Heart Rate Variation). Using valence, arousal, dominance model, 8 different emotional states namely relaxed, peaceful, bored, disgust, nervous, sad, surprise and excited was classified. The classification accuracy of SVM, NN and LR model are calculated and compared.

The introduction of automated emotion recognition techniques in human-computer interaction applications could significantly increase the quality of the user experience and lead to more emotional-aware computer interfaces.

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