Human Emotion Recognition using Electrocardiogram Signals

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Abstract— Human emotions are recognized using face recognition, speech recognition, physiological signals recognition etc. This paper represents Electrocardiogram (ECG) signal for emotion recognition thorough analysis of its psychological properties to recognize human emotion, it can reflect people's true emotion and provide smooth interface between human and computer. Each signal is empirically decomposed by using Empirical Mode Decomposition (EMD) into finite set of small oscillatory activity called Intrinsic Mode Functions (IMF's). The information components of interest are then combined to create feature vector based on the combination methods for exploiting the fission-fusion processes provided by Hilbert-Huang transform. In the next stage, classification is performed by using Multi class Support Vector Machines to identify four emotional states (joy, anger, sadness and pleasure) of human body. When we evaluated the algorithm on database recorded at university of Augsburg, the proposed method achieved improved recognition accuracy for subject-independent classification.

Keywords- *Hilbert-Huang Transform (HHT), Empirical Mode Decomposition (EMD), Electrocardiogram (ECG), Intrinsic mode function (IMF).*

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I. INTRODUCTION:

The ability of computer to understand human emotion and provide appropriate action is one of the key focus areas of research in the interaction between humans and intelligent machine more natural. It will increase application area in medical and education field for e.g. during online learning, the receptiveness of the student will be greatly increased if the computer knows the students emotional state and provides the appropriate learning. A psychologist can diagnose the disease easily with the knowledge of the patient's emotional state. Applications can be extended to missions involving very aged people, new born, patients with Autism etc, who will not be able to express their emotions explicitly.

Emotion recognition using physiological signal is a more complex process because of sensitivity to movement artifacts and the inability to visually perceive emotion from data. In this paper, we proposed to combine advanced signal processing and machine learning techniques for the characterization of physiological signals. If the features extracted are carefully chosen, it is expected that the features set will extract relevant information from the input data in order to perform the desired task. There are many techniques proposed to extract features from physiological signals in the literature. The available methods are either for linear but non-stationary, or nonlinear but stationary and statistically deterministic processes. Hilbert Huang Transform (HHT) works better for nonlinear and non-stationary signals [4] so we used that method for feature extraction. The development of the HHT was motivated by the need to describe nonlinear distorted waves in detail, along with the variations of these signals that naturally occur in non-stationary processes.

II. DATABASE:

We use the data of University of Augsburg [1]. In this database, the physiological signals were recorded at the same time when the subject was listening to four different music. This music was used to induce him to feel four different emotions: joy, anger, sadness and pleasure. Emotion models for these are represented in figure 1.There are 25 signals were recorded for each emotion. Moreover, the raw signals were trimmed to a fixed length of two minute.

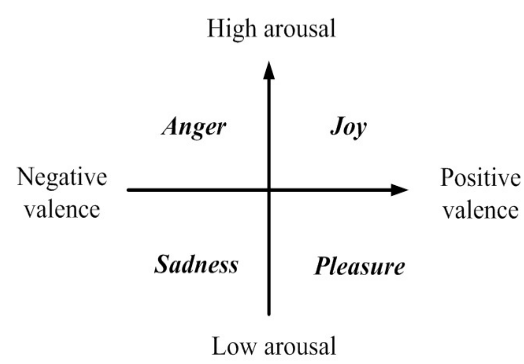

Figure 1. Emotion model

Above figure represents two common scales as valence and arousal. Valence represents the pleasantness or polarity of emotion stimuli, with positive (or pleasant) at one end and negative (or unpleasant) at the other. For example, joy has a positive valence, while disgust and anger has a negative valence. Another dimension is arousal (activation level) denotes strength of emotion. For example, sadness has low arousal, where as anger has a high arousal level.

III. METHODOLOGY

In this section, we propose a methodology based on Hilbert Huang Transform (HHT). The HHT comprises the Empirical Mode Decomposition and Hilbert transform.

A. signal Decomposition

EMD is used for signal decomposition based on Hilbert Huang Transform. Huang et al. [10] proposed the Empirical mode decomposition is adaptive and basis function of the decomposition is self defined which makes it suitable for the analysis of complex underlying phenomena. EMD method decomposed the nonlinear, non-stationary signal into a finite set of one mode oscillatory part of Intrinsic Mode Functions (IMF's). Each IMF function satisfies two conditions [10]. 1. In the whole data set, the number of extrema and the number of zero crossings must be equal or differ at most by one. 2. At any point, the mean value of the envelopes defined by the maxima and minima is zero for every sample.

These rules naturally force one mode of oscillatory activity in the IMF. The effective algorithm for the detection and extraction of IMFs is adaptive and iterative. Once an IMF is found, it is removed from the signal and algorithm iterates on the residual. The algorithm of EMD is as follows:

Let's consider x= x(t) is a given input signal,

Step1. Identify all maxima and minima of x(t).

Step 2. Interpolate between the maxima and connect them by a cubic spline curve. The same applies for the minima in order to obtain the upper and lower envelopes $e_{max}(t)$ and $e_{min}(t)$, respectively.

Step 3. Compute the mean, $m1(t) = (e_{max}(t) + e_{min}(t))/2$

Step4. Subtract the mean envelope from the signal to get the first component h1(t)

Step5. Test if h1(t) is an IMF:

a. if yes, set c1(t) = h1(t) and go to the step 6,

b. if not, replace x(t) with h1(t) and iterate steps 1-4.

Step 6. Let the residual signal r1(t) = x(t) − c1(t).

All above steps are iterated on the residual until the final Residual $r_n(t) = r_{n-1}(t) - c_n(t)$.

In above algorithm once an IMF is found, it is removed from the signal and all steps of algorithm iterated on the residual until the final residual $r_n(t) = r_{n-1}(t) - c_n(t)$ becomes a monotonic function. The stopping criteria is important for estimation of IMFs, because it set that iteration number will not be too large to break the physical meaning of the signal and to keep the operation time of the signal be acceptable. The extraction of a mode is considered as satisfactory when the stopping criteria are terminated. Standard deviation criterion:

$$SD = \sum_{i=1}^{n} \left[\frac{|r_{i-1}(t) - r_i(t)|^2}{r^2_{i-1}(t)}\right] \quad (1)$$

Where, i is number of IMFs

Based on the above algorithm, the original x(t) can be exactly reconstructed by a linear superposition:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad (2)$$

B. Feature Extraction

The IMF's are time domain signals carrying information about oscillation activity. In this work feature extraction is done by using fission and fusion process based on HHT.

i) Fission (HHT):

In fission process two features are extracted instantaneous frequency and amplitude by applying Hilbert transform on each IMF.

$$H[c_i(t)] = \frac{1}{\Pi} PV \int_{-\infty}^{\infty} \frac{c_i(t')}{t - t'} dt' \quad (3)$$

Where PV indicates the Cauchy principal value. We can define the following analytical signals,

$$Z_i(t) = c_i(t) + jH[c_i(t)] = \alpha_i(t)\, e^{j\theta} i(t) \quad (4)$$

For IMFs the instantaneous frequency $f_i(t)$ can be computed as

$$f_i(t) = \frac{1}{2\Pi} \frac{d\theta_i(t)}{dt} \quad (5)$$

ii) Fusion (HHT)

Fusion process, aim the merging the information of each IMF to compute the mean frequency. To find mean frequency use weighted mean instantaneous frequency (WMIF) of each IMFs ci(t)) with N samples is defined by,

$$WMIF(i) = \frac{\sum_{j=1}^{N} f_i(j) A_i^2(j)}{\sum_{j=1}^{N} A_i^2(j)} \quad (6)$$

The mean frequency (MNF) is defined from WMIF is as:

$$MNF = \frac{\sum_{i=1}^{n} ||a_i|| WMIF(i)}{\sum_{i=1}^{n} ||A_i||} \quad (7)$$

Along with mean frequency statistical features (min, max, standard deviation, range and median) are also extracted to generate feature vector.

IV. CLASSIFICATION

Feature vector of first four IMF's were used as classification features. From total database Fifty percent data were used for training and fifty percent for testing. Classification was performed with extension of SVM called Multi class support vector machine with one Vs rest method. Result of emotion recognition using this class is representing in next section.

V. RESULT

The ECG database recorded in University of Augsburg is shown in figure2.

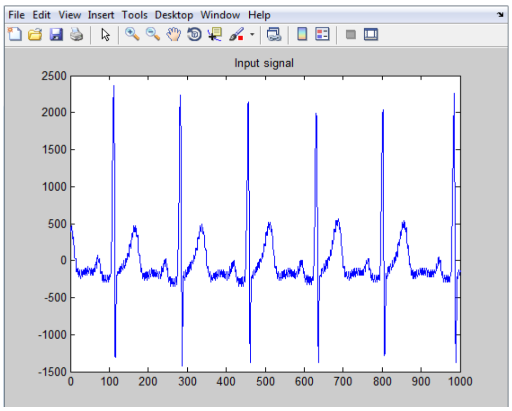

Figure 2. Recorded ECG signal

From the recorded ECG signal the baseline noise are removed by using EMD. The noise removed ECG signal is shown in the Figure 3.

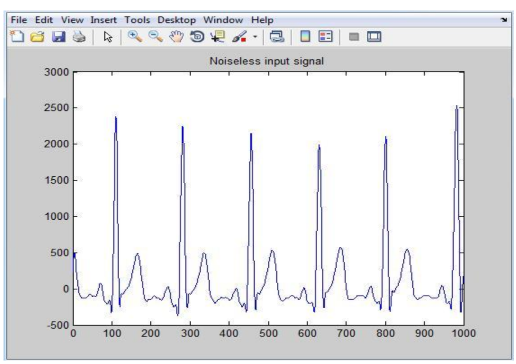

Figure 3. Noise removed ECG signal

Calculated IMFs are shown in Figure 4. First four IMFs contain oscillatory activity then last IMFs, since last IMFs can't prevent the instantaneous frequency. Number of IMF's are uncertain is shown in following figure,

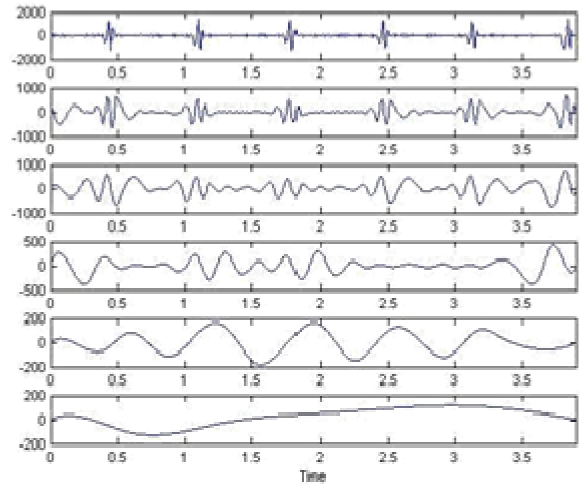

Figure 4. First six IMF signal

The 65% result of emotion recognition for second IMF using subject independent, also these results are improved by taking combination of different IMF's shown in table 1.

Table 1. Result of IMF's

Sr.No	IMF's and features	% accuracy
1	IMF 2	65
2	IMF1,2 (12features)	65
3	IMF1,3 (12features)	47.5
4	IMF2,3 (12features)	57.5
5	IMF1,2,3 (18features)	72.5
6	IMF1,2,3,4 (24features)	50

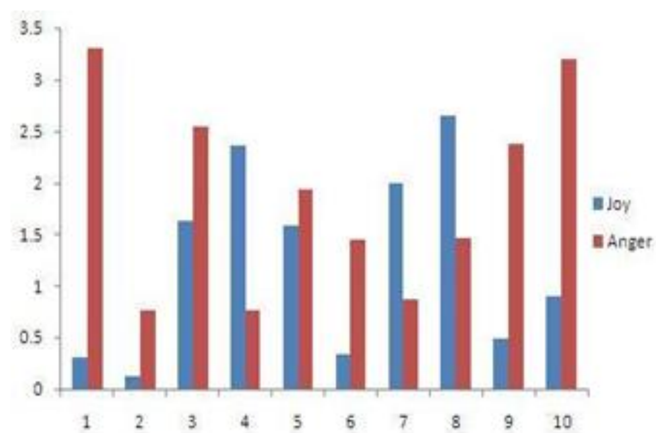

Figure 5. Comparison between joy and anger emotion.

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This bar-graph represents comparison between high arousal signals (joy and anger), calculated for mean frequency of IMF2. It results high frequency for anger then joy.

VI. CONCLUSION

Analyzed electrocardiogram signals to recognize four different emotions. Two methods fission and fusion based on the Hilbert-Huang transform (HHT) are used. The experimental results shows that proposed features extraction scheme allows to analyze the heterogeneous signals based on the estimation of mean frequency using instantaneous amplitudes and frequencies. This also shows that performance of this method depends on particular IMF and is better for second.

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