Emotion Detection in Human Beings Using ECG Signals

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***Abstract*— Emotion is often defined as a complex state of feeling that results in physical and psychological changes that influence thought and behavior. Emotion modeling and recognition has drawn extensive attention from disciplines such as psychology, cognitive science and engineering. The objective of this proposed work is to identify the emotional states of human body using ECG signals, which could revolutionize applications in medicine, entertainment, education, safety etc. A solution based on empirical mode decomposition is proposed for the detection of dynamically evolving emotion patterns on ECG. Classification features are based on the instantaneous frequency and the local oscillation within every mode. The proposed system uses the fast fourier transform to remove the noise from the synthetic generated ECG signal and therefore the emotional states were identified efficiently.**

***Index terms* —Electrocardiogram, emotion recognition, empirical mode decomposition, Hilbert-haung transform, intrinsic mode function, instantaneous frequency, local oscillation.**

I. INTRODUCTION

Emotion refers to the cognitive and behavioral strategies people use to influence their own emotional experience. It is the generic term for subjective, conscious experience that is characterized primarily by psychophysiological expressions, biological reactions and mental states. Emotion is often associated and considered reciprocally influential with mood, temperature, personality, disposition and motivation. Emotions are important in many different areas including rational decision making and purposeful behavior. The objective is to identify the emotional states by using the ECG signals. The proposed method is the efficient method to identify the emotional states using ECG signals. In the previous work the emotional states are identified by using the biosignals. The physiological signals constitute vital signs of the human body. Examples of this category include the electrocardiogram (ECG), electromyogram (EMG), electroencephalogram (EEG), galvanic skin response (GSR), blood volume pressure (BVP), heart rate variability (HRV), temperature (T), respiration rate(RR). These signals have traditionally been used for clinical diagnostics, but there is significant evidence to suggest that they are sensitive to and may convey information about emotional states. One of the benefits of detecting emotions using physiological signals is that they are involuntary reactions of the body, and as such are very difficult to mask. Among the earliest efforts for emotion differentiation using physiological signals is the work of Hasan et al [1]. A total of six emotions were studied using facial expressions and physiological signals such as the HR, left and right hand temperature, skin resistance and forearm muscle tension. Emotion induction was based on reliving experiences, which is still considered to be one of the most successful approaches to emotion elicitation. The statistical analysis was based on the change scores principle, while decision trees were used to examine emotion clustering. Despite the lack of sophisticated statistical tools, this work was a land mark to the establishment of physiological reactivity to emotion. So the next work concentrates on detecting emotions from the ECG signals. It uses the dynamic generation model for generating the synthetic ECG signal. The main drawback of using this method is that, it cannot identify the correct emotional states because of the noisy signals. To overcome this drawback the proposed system uses the fast fourier transform to remove the noise from the signals.

II. THE PHYSIOLOGY OF ECG

Electrocardiogram (ECG) signals are among the most important sources of diagnostic in healthcare. The ECG signal is recorded by attaching electrodes on the surface of the body using the standard 12 lead ECG systems. The normal ECG is composed of a P wave, a QRS complex and a T wave shown in Fig. 1. The P wave is the first wave of the electrocardiogram and represents the spread of electrical impulse through the atrial musculature (activation or depolarization). There are several abnormalities that should be noted. Increased amplitude usually indicates atrial hypertrophy and is found especially in A-V valvular disease, hypertension, cor-pulmonale and congenital heart disease. Increased width often indicates left atrial enlargement or diseased atrial muscle. Absence of P waves occurs in A-V nodal rhythms and S-A block. The PR interval is measured from the beginning o the P wave to the beginning of the QRS complex. It reflects the time taken by the impulse to travel the travel the entire distance from the SA node to the ventricular muscle fibers. The normal duration for this is 0.12-0.20 seconds. The highest amplitudes of the high frequency components are found within the QRS complex. In past years, the term high frequency, high fidelity and wideband electrocardiography have been used by several investigators to refer to the process of recording ECGs with an external bandwidth of up to 1000 Hz. Several investigators have to analyze HF-QRS with the hope that additional features seen in the QRS complex would provide information enhancing the diagnostic value of the ECG.

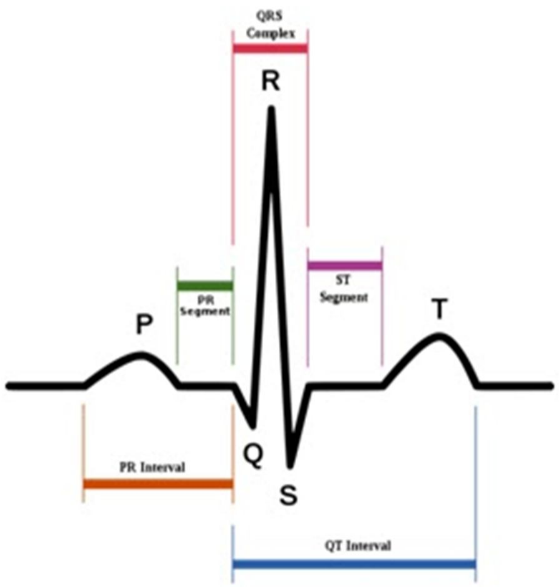

Fig. 1 Normal persons ECG signal

Probably the most important complex in the electrocardiogram is the QRS. It represents the spread of the electrical impulse through the ventricular muscle (depolarization). The upper limit is variable from lead to lead, but generally is between 20 and 30 mm. Many factors can affect the amplitude besides the health of the heart, such as chest size, chest wall thickness, emphysema. The S-T segment follows the QRS complex. The T wave represents the period of recovery for the ventricles (depolarization).

III. METHODOLOGY

The proposed methodology for ECG feature extraction is based on Empirical Mode Decomposition (EMD) which uses the fast fourier transform to remove the noise from the ECG signal and uses the Hilbert-Haung Transform for extracting the features from the ECG signal. EMD is a method of breaking down a signal without leaving the time domain. EMD filters out functions which form a complete and nearly orthogonal basis for the original signal. Completeness is based on the method of the EMD; the way it is decomposed implies completeness. The functions, known as Intrinsic Mode Functions (IMFs), are therefore sufficient to describe the signal, even though they are not necessarily orthogonal. For some special data, the neighboring components should be orthogonal for all practical purposes. The fact that the functions into which a signal is decomposed are all in the time-domain and of the same length as the original signal allows for varying frequency in time to be preserved. Obtaining IMFs from real world signals is important because natural processes often have multiple causes, and each of these causes may happen at specific time intervals. This type of data is evident in an EMD analysis. The proposed framework is comprised of four independent steps as shown in the fig. 2

1. ECG synthesis, wherein an ECG signal $x(t)$ is generated. From the data base the ECG data's were collected. From the ECG raw data's the synthetic ECG signal was generated.
2. The fast fourier transform can be used to remove the noise from the synthetic ECG signal for accurate emotion detection.
3. Estimation of the oscillatory modes, called Intrinsic Mode Functions (IMF) which can be found by using EMD algorithm.
4. Extraction of features associated with the instantaneous frequency and the local oscillation of the IMFs and classification among predefined affect states.

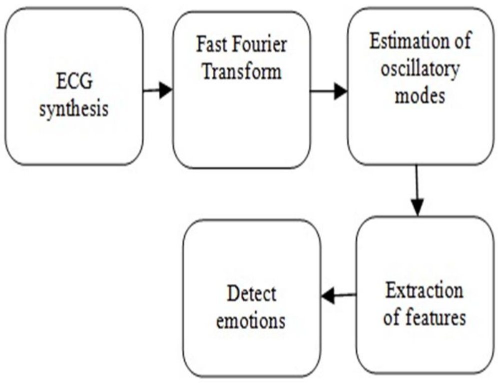

Fig.2 Block diagram of proposed work

A. *ECG synthesis*

In ECG synthesis the synthetic ECG signal was generated. From the data base the ECG raw data were collected, by using these data's the synthetic ECG signal was generated.

B. *Fast fourier transform denoising*

The FFT is one of the cornerstone routines use in signal processing as it can be used to eliminate repetitive signals from the source data. The aim of this, is to de-noise the ECG signal.

C. *Estimation of oscillatory modes*

In this section, we propose a novel method based on the Hilbert-Haung Transform (HHT) [3] to analyze physiological signals. The fundamental part of the HHT is the empirical mode decomposition (EMD) method. Using the EMD method, any complicated data set can be decomposed into a finite and often small number of components, which is a collection of intrinsic mode functions (IMF). An IMF represents a generally simple oscillatory mode as a counter part to the simple harmonic function. By definition, an IMF is any function with the same number of extrema and zero crossings, with its envelopes being symmetric with respect to zero. The definition of an IMF guarantees a well-behaved Hilbert Transform of the IMF. This decomposition method operating in the time domain is adaptive and highly efficient. Since the decomposition is based on the local characteristic time scale of the data, it can be applied to nonlinear and nonstationary processes.

The algorithm for the detection and extraction of IMFs is adaptive and iterative. One an IMF is found, it is removed from the signal and algorithm iterates on the residual in order to find more oscillatory modes. Fast oscillation is detected first. Give a signal $x(t)$, EMD operates as follows:

1. Detect local maxima $x_{max}(i)$ and minima $x_{\min}(j)$ of $x(t)$.
2. Interpolate among $x_{max}(i)$ to get an upper envelope $x_{up}(t)$ and $x_{low}(t)$ for minima.
3. Compute the average of envelopes $m(t) = \frac{[x_{up}(t)+x_{low}(t)]}{2}$.
4. Subtract from signal $u(t) = x(t) - m(t)$.
5. Iterate for $x(t) = u(t)$.

This is a sifting process, which is terminated when $u(t)$ meets the IMF criteria. If it does, $u(t)$ will be describing a underlying oscillation of $x(t)$, referred to herein as $d(t)$. EMD continues with sifting on the residual $r(t) = x(t) - d(t)$. The original signal can then be expressed as

$$x(t) = \sum_{i=1}^{N-1} d_i(t) + r(t)$$

Where $d_i(t)$ denotes the i[th] IMF extracted from the signal $x(t)$ and $r(t)$ is the final residual. By definition $r(t)$ is not an IMF. Fig. 3 shows an example of the resulting IMFs when EMD is applied on a synthetic signal x_s(t) which is an idealized, noise free waveform.

It has been observed that the first few IMFs carry quasi periodicity property of ECG. Since every heart beat has three distinct waves in the absence of noise, the first IMF is expected to exhibit three oscillatory components (tricomponent), primarily characterizing the behavior of the QRS complex. This is because the QRS complex contributes to the highest frequencies of the ECG. The first IMF, as shown in Fig. 3 decipts the fastest oscillating component of the signal. Once this is removed, the second and third IMFs exhibit bicomponent and monocomponent oscillations, respectively.

As the IMF order increases, the strength of the oscillation decreases. However, for noise-free ECG, IMFs of order higher than three are almost zero and will be ignored hereafter. As stated before, the EMD encounters problems with regard to uniqueness. The number and type of IMFs generated by EMD are uncertain, even for signals with similar statistics. For instance, the decomposition would result in more IMFs and in stronger oscillations if there was high frequency noise in the signal. This restricts the utility of

EMD as it renders comparisons among different ECG signals meaningless. Predetermining the number IMFs (by forcing decomposition to stop) defeats the purpose of EMD as the analysis will no longer be adaptive, nor will the IMFs have physical meaning.

D. Feature extraction

The ECG feature extraction system provides fundamental features (amplitude and intervals) to be used in subsequent automatic analysis. In recent times, a number of techniques have been proposed to detect features. The previously proposed method of ECG signal analysis was based on time domain method. But this is not always adequate to study all the features of ECG signals. Therefore the frequency representation of a signal is required. The deviations in the normal electrical patterns indicate various cardiac disorders. Cardiac cells, in the normal state are electrically polarized. ECG is essentially responsible for patient monitoring and diagnosis. The extracted feature from the ECG signal plays a vital in diagnosing the cardiac disease. The development of accurate and quick methods for automatic ECG feature extraction is of major importance. Therefore it is necessary that the feature extraction system performs accurately. The purpose of feature extraction is to find as few properties as possible within ECG signal that would allow successful abnormality detection and efficient prognosis. In this work, we use two types of features—the Hilbert instantaneous frequency and a measure of local oscillation.

E. Instantaneous frequency

Instantaneous frequency is defined mainly the Hilbert Transformation (HT), and time-frequency techniques. The IMFs have a vertically symmetric and narrow band form, that allow the second step of the HHT to be applied the Hilbert transform of each IMF. As explained below, the Hilbert Transform obtains the best fit of a sinusoid to each IMF at every point in time, identifying an instantaneous frequency (IF), along with its associated instantaneous amplitude (IA). The IF and IA provide a time-frequency decomposition of the data. The transform is defined as the convolution of a signal with $h(t) = \frac{1}{\pi t}$. For each of the IMFs $d_i(t)$, the Hilbert Transform is applied as follows:

$$H[d_i(t)]=\frac{1}{\pi}\ \mathrm{P.V}\int_{-\infty}^{+\infty}\frac{d_i(\tau)}{t-\tau}d\tau$$

Where P.V indicates the Cauchy Principal value. We can define the following analytical signals:

$$z_i(t) = d_i(t) + jH[d_i(t)]$$

Which can be rewritten as

$$z_i(t) = y_i(t)e^{j\theta_i(t)}$$

Where $y_i(t)$is the magnitude. For IMF i the instantaneous frequency can then be computed as

$$f_i(t) = \frac{\frac{1}{2\pi}d\theta_i(t)}{dt}$$

essentially, $f_i(t)$ is a measure of changeability within every IMF.

F. Local oscillation

Oscillation is the repetitive variation, typically in time, of some measure about a central value (often a point of equilibrium) or between two or more different states. Modeling the type of oscillation within an IMF is a difficult problem due to the empirical nature of EMD. For every IMF $d_i(t)$, let u_i and v_i be the time instances of the maxima and minima respectively. By definition (of IMFs), there is one zero crossing between every pair of consecutive extrema and the objective is to define the rate of interchange.

The local oscillation $\rho_i(t)$ is then computed from $y_i(t)$ with normalization across al IMFs as follows:

1. For an element u_k^i of u_i examine $d_i(t)$ in the interval between two consecutive maxima $d_i(u_i^k), d_i(u_i^{k+1})]$.
2. Compute max-to-min and min-max transition times:
$$a = v_i^k - u_i^k, b = u_i^{k+1} - v_i^k$$
3. $y_i(t) = \min(a, b)\ , u_i^k \le t \le u_i^{k+1}$

$$\rho_i(t) = [1 - y_i(t)]/A$$

Where A is the maximum of all $\rho_i(t)$, i.e., local oscillation is normalized across all IMFs.

RESULTS AND DISCUSSION

The ECG raw data was collected from the MIT/BIH data base. Using these ECG raw data's the synthetic ECG signal was generated. The generated ECG was shown in the Fig. 3

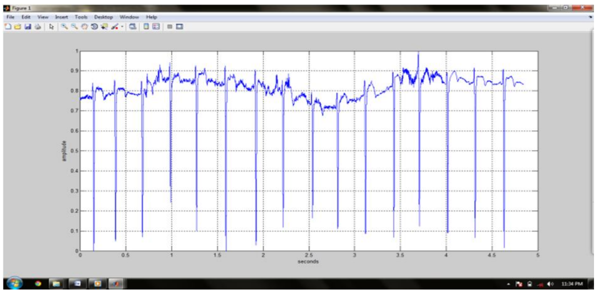

Fig. 3 Generated synthetic ECG signal.

From the synthetic ECG signal the noise are removed by using the fast fourier transform technique. The noise removed ECG signal is shown in the Fig. 4

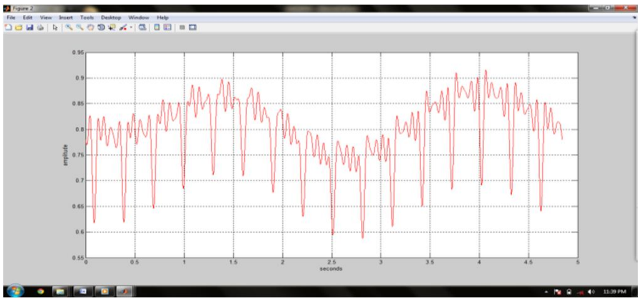

Fig. 4 Noise removed ECG signal

After noise removing process, the noise removed signal is converted into raw data's, and it is given to the EMD algorithm to generate the IMF signals.

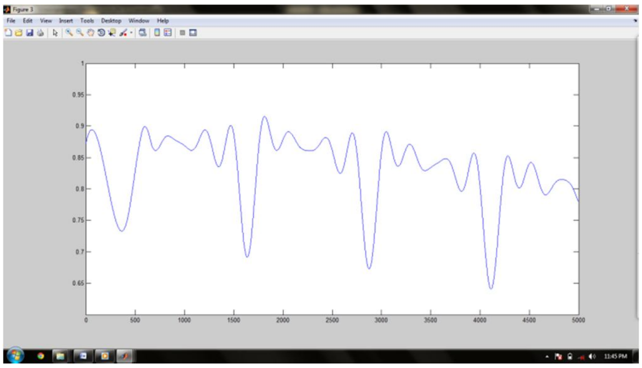

Fig. 5 First IMF signal

From the IMF signals we will consider any one of the first three IMF signals, because other IMF signals have less oscillatory activity, they will not prevent the instantaneous frequency and local oscillation activity.

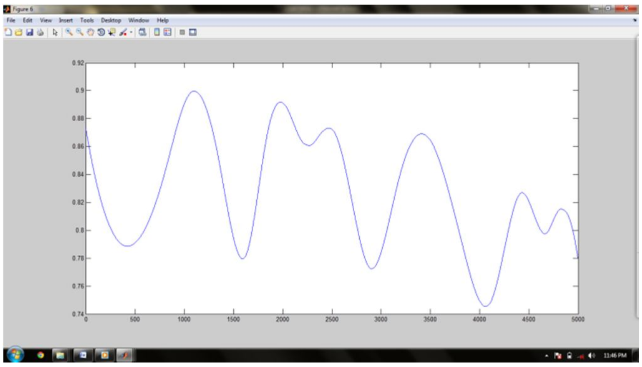

Fig. 6 Second IMF signal

From the IMF signal we want to find the amplitude and instantaneous frequency. Based on the frequency and amplitude we can classify the emotion of human beings.

For the joy persons ECG signal the instantaneous frequency is between (10 Hz-40Hz) and the amplitude is in between (0.2mv-0.25mv). When the amplitude and instantaneous frequency fall above and below the particular limit, it shows the fear, angry and sad emotional states. For the sad emotional state the instantaneous frequency is below (10-40) Hz, and the amplitude is below (0.2-0.25) mv, and for the anger emotional state the instantaneous frequency and the amplitude is beyond the particular value, ie., the instantaneous frequency is above (40-100) Hz and the amplitude is above 1.5 mv. For the fear emotional state the instantaneous frequency is in between (40-100) Hz and the amplitude is, between the limit (0.3-1.5) mv.

Emotional states	**Instantaneous frequency (Hz)**	**Amplitude (mv)**
Joy	(10-40)	(0.2-0.25)
Sad	Below 10	Below 0.2
Fear	(40-100)	(0.3-1.5)

Anger	Beyond 100	Above 1.5

CONCLUSION

In emotion research, it is very important to collect meaningful data. This technique is an efficient method to determine the emotional states of human beings. 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.

REFERENCES

[1] A. Arafat and K.Hasan, "Automatic Detection of ECG wave Boundaries using Empirical Mode Decomposition " Proc. IEEE Int'l Conf. Acoustics, Speech and Signal Processing, pp.461-464, 2009.

[2] Leslie Cromwell, Fred J. Weibell, Erich A.Pfeiffer. "Biomedical Instrumentation and Measurement".

[3] C.Zong and M.Chetouani. "Hilbert-Haung Transform Based Physiological Signals For Emotion Recognition" Proc.IEEE Int'l symp. Signal Process Letters, vol.14,no.12,2009.

[4] J.Pan and W.J.Tompkins, "A Real-Time QRS Detection Algorithm" IEEE Trans. Biomedical Eng.,vol.32,no.3,pp.230-236,2004.

[5] M.Jones and T.Troen, "Biometric Valance and Arousal Recognition"Proc.19th Australasian conf.Computer-Human Interaction. pp.191-194, 2007.

[6] F.Honig, A.Batliner, "A. Batliner, "Real-time recognition of the affective user state with Physiological signals" Proc.Doctral Consortium Conf.Affective Computing and Intelligent Interaction. pp.1-8,2007.

[7] Foteini Agrafioti and Dimitrios Hatzinakos, "ECG pattern analysis for emotion detection" Proc. IEEE transaction on affective computing, vol.3, No.31,2012.

[8] F.Naser,K.Alvarez and C.L. Lisetti, "Emotion Recognition from physiological signals using wireless sensors for presence technologies" Int,l J. Cognition, technology and work special issues on presence, vol.6, no.1, pp.4-14,2004.

[9] M.Blanco-velasco, B.Weng and K.E. Barner, "ECGnsignal denoising and baseline wander correction based on the empirical mode decomposition"Computer in biology and medicine, vol.38,pp.1- 13,2008.