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Improved Performance of Human Emotion Detection Using ECG Signal Processing

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Abstract: ***Simulation and identification of emotions have attracted much interest from fields like cognitive science, psychology, and, recently, engineering. Even though a good quantity of investigation has been conducted on behavioral modalities, there are some under-researched aspects such as physiological signals. This research brings forth the ECG signal and introduces a complete study of its psychological characteristics. The very institution of this signal as a biometric property justifies subject-reliant emotion identifiers that record the immediate changeability of the signal from its homeostatic standard level. We are enhancing the implementation of the Emotion Identification through the application of ECG signals in this work. We recommend Ensemble Pragmatic Mode Decomposition or EPMD technique to diminish the operation duration and enhance the categorization rate.***

Keywords: Electrocardiogram, emotion recognition, affective computing, arousal, valence, active stress, passive stress, bivariate empirical mode decomposition, intrinsic mode function, instantaneous frequency, oscillation.

1. Introduction

People's emotions are psychophysiological occurrences that impact every facet of our day-to-day routine. Emotions are intricate operations composed of many elements, counting physical modifications, feelings, cognitive responses, actions, and reflections. Different models were recommended by taking into account the manners that these elements interact to generate emotions, though right now there is no unique method that is unanimously recognized. Simulating emotions is a really tough issue that has attracted a significant amount of attention from the developing area of human-computer interaction. The aim is to devise frameworks that may spontaneously recognize emotional phases, and which can modernize uses in the medical field, education, entertainment, protection, and so on. The major issue in devising such designs resides in our dependency on perceptible demonstrations of emotions to create and substantiate them as the dormant aspects that produce emotions are imperceptible.

The primary phase in simulating any occurrence is information acquisition. We have to devise trials and introduce techniques that effectively incite emotions within a laboratory environment wherein we may save and acquire psychological information. When measuring psychological activity, we are restricted to the analysis of perceptible occurrences such as facial expressions, voice characteristics, gestures, and so on. Such modalities are common in HCI as they utilize similar prompts that people depend on to sense and identify emotional states. Furthermore, the majority of people show comparable manifestations as a consequence to similar emotional incitement, which permits for impartial emotion elucidation.

One main disadvantage of utilizing behavioral modalities to sense emotions is the doubt that comes up for people who either are purposely controlling their emotional manifestations or are inherently emotionally suppressive. For example, even though facial expressions may be studied to deduce emotions, this does not assure that a person will manifest the equivalent prompting, regardless of whether they are feeling a particular emotion. This has grave impacts in some uses like observation. Physiological signals or biosignals are an attractive substitute to the utilization of behavioral modalities as they comprise of crucial signs of a person's body. Instances in this classification count the electrocardiogram or ECG, electroencephalogram or EEG, electromyogram or EMG, galvanic skin response or GSR, heart rate (HR) or heart rate variability (HRV), blood volume pressure or BVP, respiration rate or RR, and temperature or T. Such signals have customarily been utilized for medical diagnostics, though there is consequent proof to imply that they are responsive to and can transmit data concerning emotional states [1-6]. Among the advantages of sensing emotions by utilizing biosignals is that they are the body's reflexive responses, and hence are really tough to conceal.

Furthermore, for the length of time that the detectors are connected to the body, such signals are saved constantly, permitting numerous emotional evaluations. This is contrary to voice characteristics, for instance, which may be recorded just when the person is talking.

Though, there are numerous hypothetical and realistic issues with respect to physiological signal founded emotion sensing. Firstly, even though the proof implies that biosignals are impacted by emotions, the actual impacts on the waveform designs have yet to be observed. For instance, the heart rate rises both when someone is afraid and when excited, however, whether we may separate the two is till now obscure. Secondly, there are open queries concerning the subject-dependent aspect of these impacts.

Aside from the open hypothetical queries, there are also realistic challenges. The preliminary conventions are much more intricate compared to behavioral emotion investigation, where the acquisition is helped by notifying subjects to show emotions. For physiological signals founded trials, more advanced procedures are required to evoke honest emotions in a laboratory environment. Moreover, naming biosignals is subjective and hence, really uncertain owing to the hardship in instituting the basic truth. One more realistic issue concerns the signal recording. The acquisition operation is more intrusive in contrast to that for behavioral modalities as the detectors have to be connected to the subject's body for the length of an information acquisition session. It is for this cause that it is essential to reduce to a minimum the quantity of information needed for this work, that is, for sensing to depend on the minimum possible signals.

Dissimilar biosignals come from various areas of a person's body and can explain disconnected functions. For example, the electrocardiogram and blood volume pressure signals come from cardiovascular source, whereas the electromyogram concerns muscle electrical potential. Exploring the actions of each signal is essential so as to unambiguously institute its boundaries in evaluating psychological activity. For example, we expect that the just the trial settings can incite emotional response for one physiological signal, though cannot incite some others.

2. Related Research

There are many techniques in the base paper for physiological signal founded emotion sensing, generally categorized here into two classes depending on the manner the emotional models are imagined and arranged.

The initial class counts the DEM or Discrete Emotional Models, where the aim is to identify and name regular emotional phases (for example happiness, moroseness, or fear). Such techniques depend significantly on the basis that a random emotional phase is distinct and fully discernible from the rest.

Conversely, ADM or Affective Dimensional models alleviate the requirements for discrete emotions and consider any emotional phase as a mixing of two boundaries, that is, arousal and valence. Arousal is a gauge of emotional incitement (intensity) and it changes between low and high. Valence is a gauge of congeniality for the felt emotion, varying from really congenial (positive) to really disagreeable (negative). A two-dimensional area (the AV plane) is formed from these two variables, and in ADM, designs categorization is conducted among preset regions of the plane.

From the viewpoint of engineering, the two techniques both have benefits and demerits. For example, DEM designs may be effortlessly envisaged and suited to uses, though, each emotion has to be completely characterized and suitably aimed by the trial configuration, which can be uncertain for surrounding emotions (for instance, congeniality and serenity). The rest of this part gives a short summary of some of these techniques; with the aim of showing the manner that ECG has formerly been arranged.

3. Signal Processing for Emotion Detection

There are two major issues that crop up with signal processing of biosignals when aiming for the categorization of emotion patterns. Firstly, emotion-particular patterns are not distinct for physiological signals. Secondly, it is usually doubtful if emotions have been shown at all. Most of the past researches on ECG signals concur that emotion display is inherently individual-specific, notwithstanding the accounts concerning cardiovascular response to emotion in which there are questionable observations on the different waveform patterns.

We dispute that general emotion sensors of ECG signals carry the uncertainty of being incorrect for the two causes below:

- ECG has been instituted as a biometric property [30-31], which implies that automatically it holds individual-specific data. The occurrence of a certain heart beat relies on a quantity of reasons, like the geometry and direction of the heart muscle, the conductivity of different regions of the heart, the activation stimuli [32], and the person's habitus or sex [33-35]. This bodily feature of ECG made a robust foundation for the research and institution of its biometric characteristics (that is, its utilization in discerning people for identification purposes) [30-31].

- Various individuals feel emotions in dissimilar manners. Even if we disregard the biometric feature of the ECG signal, there is significant ANS innervations change in a populace [17].

For these causes, emotional patterns are in this sensed as changes from the usual look of a person's ECG signal. We execute characteristic retrieval in the time field for two purposes—the time-field signals are noted to be capable in terms of emotion particular characteristics [36], and it is hazardous to compel stationarity and linearity constraints which are required for Fourier transform on ECG [37]. Moreover, as we may not foresee the impacts of emotional operations on the ECG signal, there is the danger of overlooking the active variations caused by emotions if we utilize schemes that depend on preset foundations. We are more concerned with the manner that features of the ECG signal change over numerous heart-beats when someone feels various emotions. The neighboring features of any specific pulse are of minor appeal. Concerning this, the EMD or Empirical Mode Decomposition [37] is a prevailing instrument as it is active, information stimulated, and studies the signal holistically to emphasize essential tendencies. With no suppositions beforehand about the characteristics of the signal, EMD adjusts to the integrated oscillatory activity and disintegrates ECG into a quantity of basic modes. We believe that comprehending the basic modes that are concealed in the cardiac oscillatory activity is an important primary phase in any trial to categorize psychological states.

4. Proposed Methodology

Disjoining the buzz from the ECG signal aids in getting the bare ECG signal and is effective in the case where the ECG signal is not observed regularly by the particular instruments. There are numerous techniques that give sensible outcomes for disjoining buzz from the ECG signal, though there are a few disadvantages such as utilizing the multichannel ECG signal, greater signal to noise ratio – being strong, and so on. In this scheme, we surmount the disadvantage by utilizing solitary – channel ECG as shown in Fig. 3 to get the information on higher order statistics, the prominent aspect from traditional schemes. To emphasize the restrictions of wavelet method and to highlight the various performances, EPMD and HHT methods are applied. Thus, to observe the ECG signal, the EPMD calculation is ultimately important.

Wavelet transforms

The ECG signal is disintegrated by utilizing wavelet transform founded on the series of bases function. There are a couple of boundaries that basis vector function relies on: (a) the dilation coefficient, and (b) the translation step. The initial signal is retrieved by condensing or expanding and translating the wavelet function ψ (t).

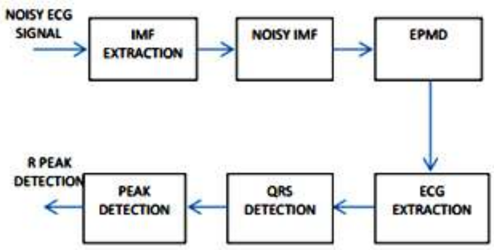

Figure 1: Block Diagram of Proposed System

B. Ensemble Pragmatic Mode Decomposition

The time pattern is disintegrated into separate elements in EPMD method since in wavelet method where structural and neighboring chronological features are developed. Debuzzing by utilizing EPMD is realized from the source ECG signal from the total of estimations. In this case we have studied the univariate time pattern for the method of EPMD. In the EPMD method, the initial ECG signal is estimated as the total of linear elements. EPMD method is utilized to disintegrate the signal into inherent mode function and remains. EPMD is initiated by approximating the total of both the elevated frequency and the inferior frequency elements locally like illustrated in Fig. 4 which shows the flowchart of EPMD method. The elevated frequency elements are inherent mode functions and inferior frequency elements are remains. IMF and remains are retrieved constantly. The IMF and remains are summed when the disintegration ends. The debuzzed signal with EPMD method is as depicted in Fig. 2.

C. ECG Signal Extraction

EPMD calculation is used to retrieve the ECG signal from trial signal after the step of pre-processing. EPMD demonstrates superior execution and the noted RS signal retrieved from sample 1. Three dissimilar requirements for recording, namely supine, standing, and light activity, were studied. The SNR value computed from the debuzzed ECG signal is superior to alternative traditional techniques. The signal retrieval gives more data on the sicknesses. D.

D. QRS Detection

Electrocardiogram (ECG) signal indicates the contractile activity of the heart and this is the heart's electrical expression. The ECG signal is corrupted whilst recording with artifacts and buzz which may be inside the concerned band (0.5 – 100 Hz), where EMG, PLI or Power-Line Interface, and baseline wander impacts are the artifacts that are most frequently experienced. The interceptions such as baseline-wander and PLI are rectified and removed from ECG signal by utilizing EPMD method correspondingly. The inherent mode function has neighboring maxima and neighboring minima from which the buzz is eliminated.

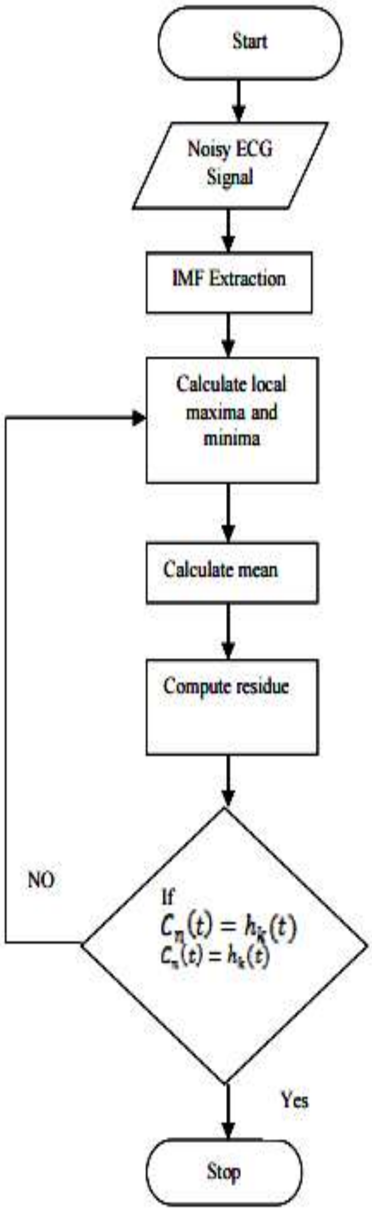

Figure 2: Flow chart for signal extraction

5. Results

In the Results Section, Three CASE-I, II & III are showing the results comparison for the BEMD (Bivariate Empirical Mode Decomposition) method and Proposed EPMD (Ensemble Pragmatic Mode Decomposition) method.

Case-1

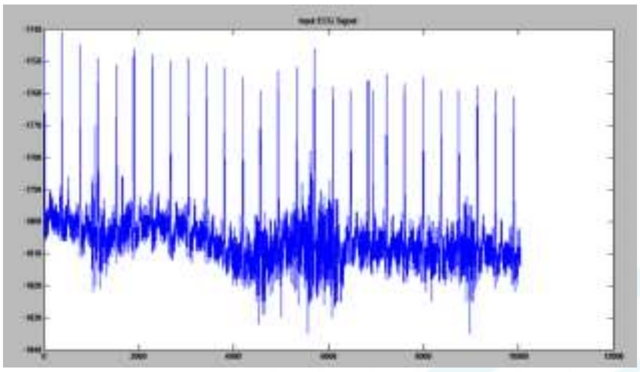

Figure 3: Input ECG signal

Figure 3 is showing the input ECG signal for the classification and processing time.

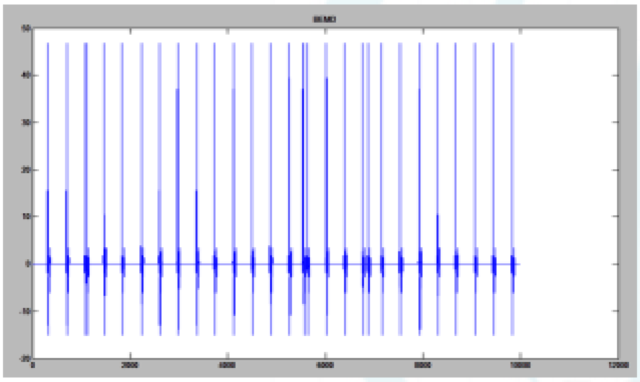

Figure 4: BEMD ECG signal

Figure 4 is showing the BEMD ECG signal which receive after complete the process of the BEMD Method.

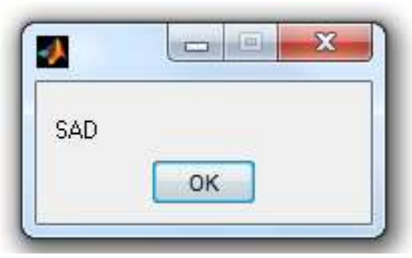

Figure 5: Emotion Detection

Figure 5 is showing the Emotion Detection. In this Figure, it is showing the Popup of the SAD Emotion Detection.

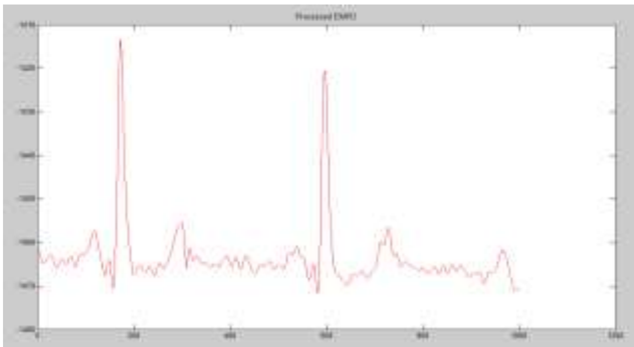

Figure 6: EMPD based ECG signal

Table 1: Comparison Table

Method	Classification Rate (%)	Processing Time (s)
BEMD	34.9171	37.6829
EPMD	51.2404	2.7059

Table 1 is showing the comparison table for BEMD (Bivariate Empirical Mode Decomposition) method and Proposed EPMD (Ensemble Pragmatic Mode Decomposition) method. As Results are showing EPMD classification Rate is high and Processing Time is low as compare to BEMD.

Case-2

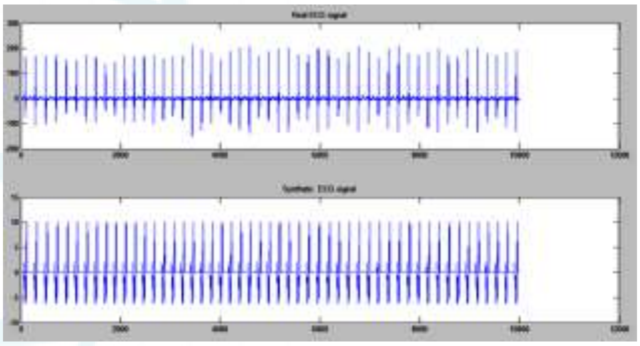

Figure 7: showing the Real ECG signal and Synthetic ECG signal

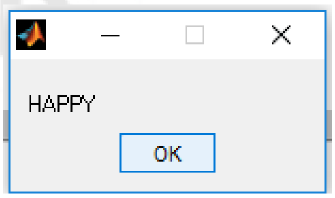

Figure 8: Emotion Detection

Figure 8 is showing the Emotion Detection. In this Figure, it is showing the Popup of the HAPPY Emotion Detection.

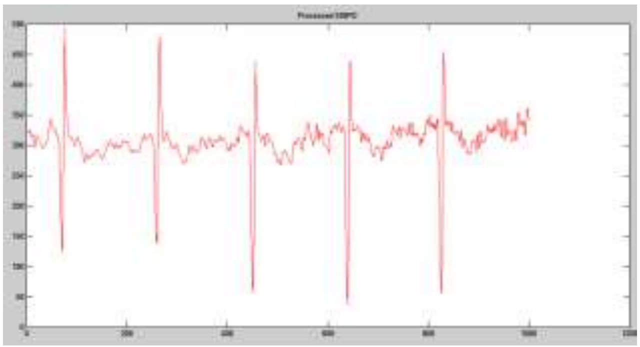

Figure 9: EMPD based ECG signal

Table 2: Comparison Table

Method	Classification Rate (%)	Processing Time (s)
BEMD	34.0711	58.5701
EPMD	41.2699	5.1495

Table 2 is showing the comparison table for BEMD (Bivariate Empirical Mode Decomposition) method and Proposed EPMD (Ensemble Pragmatic Mode Decomposition) method. As Results are showing EPMD classification Rate is high and Processing Time is low as compare to BEMD.

Case-3

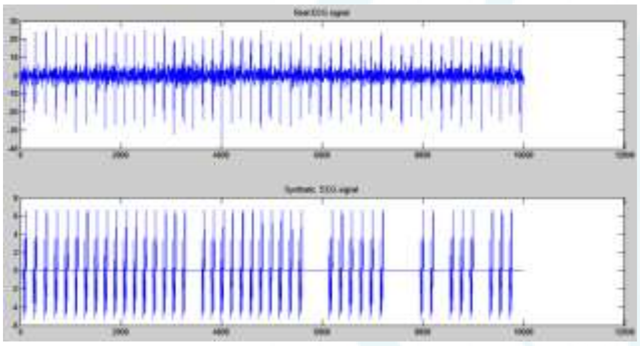

Figure 10: showing the Real ECG signal and Synthetic ECG Signal

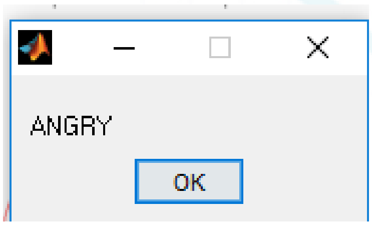

Figure 11: Emotion Detection

Figure 11 is showing the Emotion Detection. In this Figure, it is showing the Popup of the ANGRY Emotion Detection.

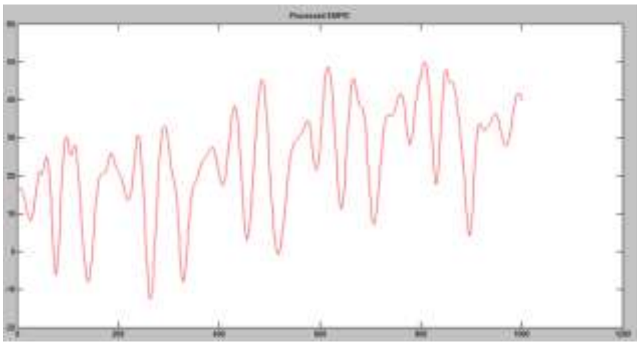

Figure 12: EMPD based ECG signal

Table 3: Comparison Table

Method	Classification Rate (%)	Processing Time (s)
BEMD	15.2413	56.8344
EPMD	49.1338	2.3451

Table 3 is showing the comparison table for BEMD (Bivariate Empirical Mode Decomposition) method and Proposed EPMD (Ensemble Pragmatic Mode Decomposition) method. As Results are showing EPMD classification Rate is high and Processing Time is low as compare to BEMD.

6. Conclusion

In this Research, improve the ECG Emotion Signal Detection. It will Decrease the False Detection Ratio. As results are showing the Classification Rate is increasing for the EPMD method while processing time is decreasing for the EPMD method as compare to BEMD.

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