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A Physiological Signal Analysis Algorithm for Human Stress Recognition from ECG Signal

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***Abstract*- Our work's primary goal is to process electrocardiogram data utilizing the Fission-Fusion method of the Hilbert spectrum. One of the most effective techniques for the analysis of nonlinear and non-stationary signals is based on the Hilbert Huang Transform (HHT). We have processed Electrocardiograms (ECGs) by applying EMD after the Wavelet Packet Transform since our method is better appropriate for nonlinear and non-stationary signals (WPT). In order to produce mono-component, breakdown the ECG signal into a number of narrow band signals, and remove unnecessary IMF, WPT is applied. In order to identify human emotions in our work, we employed the Fi-Fu algorithm to analyze electrocardiogram (ECG) signals for the detection of significant parameters such instantaneous frequency, amplitude, mean frequency, and second order difference plot. The EMD procedure has the ability to handle noise seen in ECG signals. Wavelet Packet Transform (WPT) is a more practical alternative to wavelet transform in real-world scenarios including signal analysis and denoising. WPT possesses unusual localization and enhanced discerning capabilities in the high frequency domain. WPT separates the high-frequency and low-frequency components of the frequency information of the signals to be studied.**

KEYWORDS — HHT, EMD, ECG, WPT, IMF

I. INTRODUCTION (*HEADING 1*)

Human stress is a physiological reaction that manifests as a subjective, non-deterministic bodily signal. A specific emotion is inferred from the physiological reaction to the audio-visual stimulus that is employed as a triggering signal. Stress and a person's mental state, temperament, identity, nature, and motivation are frequently linked. Hormones and neurotransmitters like dopamine, noradrenalin, serotonin, oxytocin, and cortisol affect human stress [1]. The Human stress and nervous system activation are perfectly correlated. Arousal activation levels and human stress are tightly related, as well. The behavioral propensity is connected to human stress as well. The neurological system does, in fact, mirror human stress. Positive and negative stress levels can be intelligently distinguished by our neurological system. The best technique to determine how stress affects the neurological system is to analyze heartbeats. The heartbeats clearly reflect all extreme human stress, it has been determined. Throughout the past few decades, research on human stress has accelerated significantly. Human-computer interaction (HCI), disease diagnosis (medicine), human behavior (psychology), mental disorders (neuroscience), and sociology are a few of the domains that are relevant to study on human stress [2]. Excellent research on the identification of human stress was facilitated by the literature that was available and applicability in numerous fields. The biomedical research provides insight into the role that heartbeats play in the signaling process between the heart and brain. This internal communication also shapes how you see the outside environment, which has a big impact on how much stress you experience. The neuroscience of affect can be used to differentiate human stress from some comparative developments. [3, 4] Emotions are the mental condition that everyone is feeling and are merely a symbol of the stress that people experience. If we contrast stress with moods, moods manifest themselves over longer periods of time than stress and are also typically less strong. Although it is sometimes employed in opposition to stress, the word "affect" is used to collectively describe the points of stress, moods, and mental states.

Theories on the experience of stress

The Stress affects a multitude of human activities, including motivation, perception, learning, cognition, coping, creativity, attention, planning, and reasoning [5]. Human-computer interaction makes it simpler to discern human stress, making it possible for doctors to diagnose diseases by determining the patient's mental state. Apps may be expanded to address the needs of autistic individuals. To recognize the human stress, the human stress recognition system needed input. Researchers have employed a range of input signals, including gestures, audio signals, and facial photographs. All of these traditional inputs form the foundation of the systems created up to this point. The system's inputs itself are the real flaw; using facial photos, verbal signals, and gestures as inputs causes the system's performance accuracy to suffer. Physiological signals can be used as an input to the human stress recognition system to increase the performance accuracy of the system. Despite coming from the human autonomic nervous system, physiological signals cannot be consciously controlled [6]. Thus, it is not possible to suppress or hide the stress using physiological cues. Emotions, in general, are said to happen unconsciously rather than consciously.

Literature Survey

In 2003, the first system for identifying human stress was created utilizing speech and facial picture cues. Several modalities, including facial images, speech signals, and physiological signal analysis techniques, algorithms, and technological advancements linked to human emotion recognition are addressed in this research endeavor. In 2004, Kim [1] created the first system for recognizing human stress using physiological signals. This system uses a variety of input signals, including the electrocardiogram, skin conductance, and electrodermal activity, to identify human stress. The support vector machine classifier is employed to address the issue of overlapped clusters, and the author used 50 subjects in this investigation. Siirtola, P, Röning, J, et al. [2] proposed an algorithm in which the author sought to normalize the features and asserted that the results from the normalized features were superior than those from previous approaches. For the examination of the signal, the author of this study provided forty features, and this algorithm chooses the top features for recognition. Thiam, P, Kestler, H.A, Schwenker, F.[3] In this study, the author created an algorithm for a system that uses several inputs, including facial expressions, physiological signals, and speech signals. For human stress, the author separately reported the results of k-NN, DFA, and MBA. Bartolomé-Tomás, A, Sánchez-Reolid, R, Fernández Caballero, A [4]. For several experiments, the author extracted a distinct feature set. 17 characteristics were retrieved from the ECG, SKT, SC, and respiration in the first experiment, while 20 and 22 features were taken from the input signal in the second and third experiments, respectively. The sixty undergraduate students' emotions were induced using an audio-visual stimulation system. A literature review reveals that the physiological signs are ideal for identifying human emotions. The user dependent and user independent multimodal human emotion identification systems created to date. In a review of the literature, it was found that the properties Mean, Standard deviation, first derivative, high frequency and low frequency, sub-band spectrum, entropy, and QRS complex and RR interval are employed to construct human emotion identification systems. Through literature study, it is noted that following aspects left out in earlier research all these features are crucial to recognize human emotions prominently,

Instantaneous frequency and amplitude, as well as instantaneous phase. To the best of our knowledge, no confirmed work has been documented in the literature study on user independent system to distinguish human emotion utilizing the aforementioned features from ECG signal. Mean Frequency computation of IMFs (MIF) and Weighted Mean Frequency (WMIF). So, the main task at hand is to build and create a user-independent algorithm for human emotion recognition utilizing ECG information. Since many decades ago, the Fourier transform has demonstrated its aptitude, durability, and simplicity in the field of signal analysis. If the input signal is not linear and stationary, the Fourier Transform is physically meaningless. Unfortunately, the Fourier Transform is inappropriate for ECG signals since they are non-stationary and non-linear. Similar to this, the wavelet transform is a crucial processing tool in signal analysis, and it may extract features from the input signal in terms of time and frequency. Wavelet has some limitations, including interference and distortion, despite its capacity to analyze non-linear and non-stationary signals, which made it seem appropriate for electrocardiogram signal analysis. Also, because the database is so large, the analysis's wavelet transform takes much longer. Although it does a poor job of portraying the resolution in frequency at high frequencies, the Wavelet Transform is not appropriate for frequency range analysis[7]. These shortcomings led to the Hilbert-Huang transform that was suggested here to evaluate time-frequency signals. By eliminating the shortcomings of HHT, such as unwelcome IMFs in the low-frequency area that could damage the outcome, the property of mono-component that cannot be satisfied in either IMF 1 or IMF 2, and lastly low-energy components signals that cannot be used in HHT, our work is also expanded. In order to address the aforementioned shortcomings, we suggested the Modified HHT approach and applied Wavelet Packet Transform (WPT) to get frequency components with low energy at various narrow bands. All of these narrow bands will be decomposed into different IMF signals using the decomposition method EMD after wavelet packet transformation to satisfy the mono-component criterion. Decomposition in the empirical mode. The Hilbert-Huang Transform includes the Empirical mode decomposition. For nonlinear and non-stationary signals, the empirical mode decomposition is more appropriate [8]. Each nonlinear signal contains intrinsic oscillatory modes, which are referred to as the intrinsic mode function (IMF). A collection of intrinsic mode functions are sought after by the empirical mode decomposition algorithm in an effort to break down the ECG signal. There are several intrinsic mode functions present in the multi-component signal; their instantaneous frequencies are determined by estimating the IMF from the input signal [9]. An IMF is a function that satisfies two explicit IMF properties, which are as follows:

- The number of extrema and the number of zero crossings in the input signal must be identical or differ by no more than one.
- For each sample, the mean of the envelopes defined by the maxima and minima is zero.

Decide on the first component after computing a mean envelope from the input signal.

Algorithm: Empirical Mode Decomposition

1. Determine the local maximum and minimum
2: Determine the average of the upper and lower envelopes.
3: Determine the residual.
4: Continue with steps 1 through 3 until the residue satisfies the requirements for intrinsic mode function (IMF)
5. Determine the residue from the initial input signal to the IMFs, which will be the input for the following iteration.
6. Break the algorithm if the residue is a trend.

$$m_{1n}(t) = \frac{(u_{\max}(t) + l_{\min}(t))}{2}$$

$$h_{1k}(t) = X(t) - m_{1n}(t)$$

$$r_{n1}(t) = X(t) - c_n(t)$$

The original signal X(t) can be expressed as the total of all IMFs and the final residual as shown below.

$$X(t) = \sum_{i=1}^{n} IMF_i(t) + r_n(t)$$

Table 1: IMF function values

IMF1	IMF2	IMF3	…	IMFn
X(t)	$X(t)-c_1 = r_1$	$r_1-c_2 = r_2$		$r_{n-2}-c_{n-1} = r_{n-1}$
$X(t)-m_1 = h_1$	$r_1 - m_2 = h_2$	$r_2 - m_3 = h_3$		$r_{n-1}-m_n = h_n$
$h_1 - m_{11} = h_{11}$	$h_2 - m_{21} = h_{21}$	$h_3 - m_{31} = h_{31}$		$h_n - m_{n1} = h_{n1}$
$h_{11} - m_{12} = h_{12}$	$h_{21} - m_{22} = h_{22}$	$h_{31} - m_{32} = h_{32}$		$h_{n1} - m_{n2} = h_{n2}$
$h_{12} - m_{13} = h_{13}$	$h_{22} - m_{23} = h_{23}$	$h_{32} - m_{33} = h_{33}$		$h_{n2} - m_{n3} = h_{n3}$
$h_{1(k-1)} - m_{1k} = h_{1k}$	$h_{2(k-1)} - m_{2k} = h_{2k}$	$h_{3(k-1)} - m_{3k)} = h_{3k}$		$h_{n(k-1)} - m_{nk} = h_{nk}$
$h_{1k} = c_1$	$h_{2k} = c_2$	$h_{3k} = c_3$		$h_{nk} = c_n$

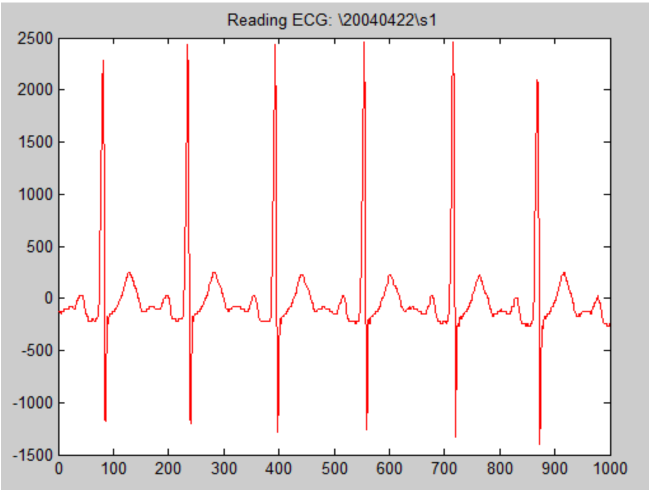

Figure 1: (a) Input Signal

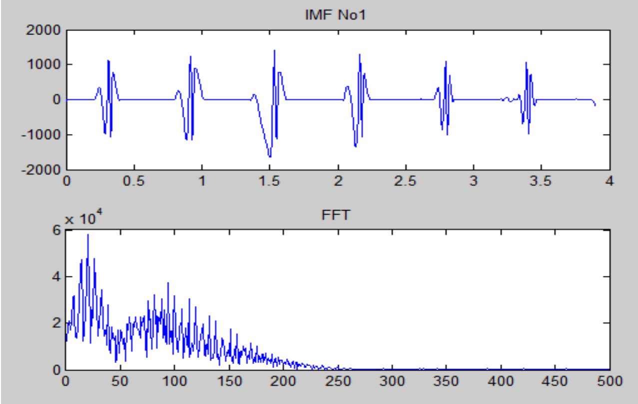

Figure 1 (a) FFT of the IMF1 of ECG signal with Joy emotion

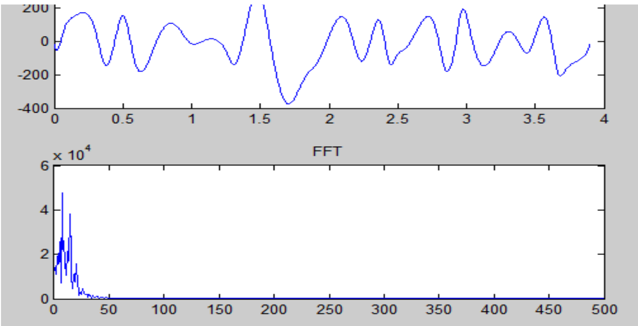

Figure 1 (b) FFT of the IMF of ECG signal

The FFT of the IMF of the ECG signal generated from the empirical mode decomposition is shown in Figure 1. (a) through (b). The aforementioned findings suggest that IMFs are crucial tools for identifying key elements of human stress. With a variable level of stress, one may observe the differences between the two IMFs. Measurements must be taken and analysed in order to characterise the physical world. The Hilbert- Huang transforms (HHT) can be used to recover the frequency components from intermittent signals that may be nonlinear and nonstationary. One of the elements of HHT is the EMD. To extract IMFs of the RR interval signal of the ECG, the empirical mode decomposition technique is used. The ECG signal is used to create the eight symmetric IMFs, which assist define the instantaneous frequency and amplitude. The database of Augsburg University in Germany served as the simulation study's work environment.

Experimental Results

It is necessary to produce reference feature vectors for each degree of stress because our work is intended to identify human stress levels. A classifier will categorize the appropriate amount of the human stress present in the subject's ECG signal if the features in the feature vector match those in the reference feature vector, which is done after comparing the feature vector with the reference feature vector. the statistical parameters obtained from the RR intervals or the difference between RR intervals through direct measurements. The standard deviation of the interval, or the square root of variance, is the easiest variable to calculate. The intrinsic mode function's standard deviation is provided in Table 2. (IMF).

Table 2: Standard deviation of intrinsic mode function (IMF).

Sr. No.	Low	Medium	High
1	24.99251	526.2624	107.9369
2	98.99719	257.5646	1429.764
3	305.8025	263.4251	89.12032
4	2100.021	257.5646	57.42847
5	877.3511	384.5184	4.27147
6	224.9999	341.1415	52.38733
7	2473.771	118.3066	566.6795
8	2500.976	497.2385	0.530225
9	188.7516	1813.076	34.58568
10	1027.65	943.2058	1.758413

Table 3: Mean frequency values of different Stress levels

Sr. No	Low	Medium	High
1	0.304708	3.305131	0.126207
2	0.121282	0.764834	2.905127
3	1.635512	2.536111	0.938395
4	2.362013	0.764834	0.500517
5	1.576845	1.931544	0.012067
6	0.32995	1.445558	0.127413
7	1.991772	0.865492	2.223825
8	2.650486	1.456903	0.002485
9	0.480475	2.375053	0.120202
10	0.894284	3.195428	0.004919

Table 3 lists the mean frequency values for various stress levels; the center frequency is represented by the mean frequency measure of IMFs of RR-interval signals. The calculations of the IMFs' mean frequency are employed in this study to distinguish between various moods.

Conclusion

The analysis of the ECG data to identify four different human emotions using the Hilbert-Huang fission-fusion technique is provided in this paper based on the transform's features. To acquire IMFs of RR interval signal of ECG, empirical mode decomposition approach-based decomposition of ECG signal is used. The ECG signal's eight total symmetric IMFs are used to define the instantaneous frequency and amplitude. Moreover, heterogeneous signals can be examined similarly to continuous signals using the suggested feature extraction scheme's calculation of instantaneous amplitudes and frequencies. The database of Augsburg University in Germany served as the simulation study's work environment. The outcomes of the trial demonstrate that HHT features outperform conventional approaches. In this study, the analysis of the ECG signal is used to identify four different emotions. The IMF1, IMF2, and IMF3 values for each emotion are different. It is clear that the IMFs 1, 2, and 3 have larger instantaneous frequency and amplitude values than the other IMFs.

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