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DETECTION OF HUMAN STRESS USING SHORT-TERM ECG AND HRV SIGNALS

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This paper introduces a method for resolving the problem of human stress detection through short-term (less than 5 min) electrocardiogram (ECG) and heart rate variability (HRV) signals. The explored methodology helps to improve the stress detection rate and reliability through multiple evidences originated in same sensor. In this work, stress-inducing protocol, data acquisition, preprocessing, feature extraction and classification are the major steps involved to detect the stress. In total, 60 subjects (30 males and 30 females) participated in the Stroop color word-based stress-inducing task and ECG signal was acquired simultaneously. The wavelet denoising algorithm was applied to remove high frequency, baseline wander and power line noises. Discrete wavelet transform (DWT)-based heart rate (HR) detection algorithm is used for deriving HRV signal from the preprocessed ECG signal. The ectopic beat removal method is employed to eliminate the ectopic beat and noise peaks in the HRV signal. In order to detect the stress, the issue of uneven sampling with the HRV signal has been successfully rectified using the Lomb-Scargle periodogram (LSP). The application of LSP in short-term HRV signals (32 s), uneven sampling issue, and power spectral information issue has been rectified and the trustworthiness of the short-term HRV signal has been proved by hypothesis as well as experimental results. Theoretical analysis suggested that a minimum 25 s of online or offline ECG data is required to analyze the autonomous nervous system (ANS) activity related to stress. In addition to the HRV signal, ECG-based stress assessment has been proposed to detect the stress through optimum features using fast Fourier transform (FFT). Various features extracted from the ECG and HRV signal have been classified into normal and stress using PNN and kNN classifiers with different smoothing factor and k values. The experimental results indicate that the proposed methodology for short-term ECG and HRV signal can achieve the overall average classification accuracy of 91.66% and 94.66% in the subject-independent mode.

Keywords: Electrocardiogram (ECG); heart rate variability (HRV); human stress detection; Stroop color word test.

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1. Introduction

Stress is a major factor in several diseases, and everyone may experience stress at some time or once in a lifetime, due to the enormous psycho-physiological demands while performing their day-to-day activities. Human stress is a kind of controllable unsteady state which can be countered by using suitable relaxation and management techniques at the appropriate time. Several studies indicate that stress is a common factor both pathogenesis, besides exacerbating the impact of many diseases, from the common cold to severe cardiovascular disease.[1] Conventionally, psychologists or medical experts have evaluated human stress levels through a set of psycho-physiological questionnaires during counseling or interview procedure. Later on, several research investigations are being undertaken to develop a more effective scientific tool for measuring stress.

Physiological signals and biochemical samples are advanced methods for measuring the stress levels.[1–10] Urine, saliva, and blood samples are the primary measures in biochemical samples to identify the effects of stress in the human body.[1–3,11] However, these biochemical samples are usually taken at various intervals of time compared with the continuous sampling of physiological signals. It is invasive and inconvenient which severely constrains its efficacy in real-time stress assessment. Conversely, physiological signals (ECG, galvanic skin response (GSR), electromyogram (EMG), electroencephalogram (EEG), blood pressure (BP), skin temperature (ST), respiration rate (RR), and blood volume pulse (BVP)) have attracted major research interest with a view to developing newer and more efficacious methodologies for measuring stress.[1–3,12]

Among the several types of physiological signals, ECG in specific heart rate variability (HRV) signals plays a vital role in stress assessment research.[1–10] Even though this signal is a major consideration, there are obstructions, such as (i) validity of short-term HRV signals, (ii) optimization of stress relevant features, (iii) frequency band selection and (iv) improving stress detection rate in subject-independent analysis using large population. Most experiments on affective state assessment, such as emotion and stress, as found in the literature, have been measured through physiological signals over shorter time intervals (less than 60 s).[13] The European Society of Cardiology has suggested that a minimum of 5 min duration is essential for measuring the heart rate (HR) from ECG signals, and that anything less than 5 min duration is of dubious value.[14] However, many emotion and stress assessment studies are based on a laboratory environment, and the effects of these affective states are so acute in nature that they have been clearly reflected in the physiological signals obtained over short periods of time (viz., from a few seconds to a few minutes).[15,16] Most studies are not concentrating upon this issue and hence conventional research methodologies are unable to detect effects of stress on HRV signals. Long-term chronic stress inducement is ethically not permitted in laboratory studies, being highly inimical to health since it involves measuring chronic stress only in day-to-day difficulties when the subjects are under severe stress. Thus, the efficacy of this short-term HRV signal needs to be investigated for detecting acute changes such as stress and emotions.

In general, the regulation in autonomic nervous system (ANS) indicates the reflection of normal HR and its variability (HRV). The ANS has two branches: sympathetic nervous system (SNS) and parasympathetic nervous system (PNS). The balance between these two systems replicates the normal value of HR, skin conductance, BP, RR, and muscle activations. During stress and relaxation, the SNS is increased, or the PNS is decreased, and vice versa. This effect is known as "cardio acceleration and retardation".[17] The acceleration of the SNS and HR is often correlated to stress. It is known that the PNS is associated with the high-frequency (HF) band (0.14−0.5) Hz, and SNS is related to the low-frequency (LF) band (0.04−0.15) Hz of HRV signal.

However, the estimation of power spectral variations above frequency bands in HRV signal requires complex mathematical procedures compared to other bio-signals. In general, HRV signals are derived either from ECG signals through the QRS detection algorithm, or directly acquired through the tachogram.[18] The following complexities are involved mainly in HRV power spectrum analysis: (i) HR variations with respect to time and (ii) inefficient detection algorithm of R peaks. These two problems cause uneven sampling, and cause ectopic beats in the signal that directly reflect the HF and LF bands which is highly sensitive to power spectral analysis of short- and long-term HRV signals.

The presence of ectopic beats and uneven sampling are the two major challenging issues in the HRV signal analysis.[18] the Lomb−Scargle periodogram (LSP) and auto regressive (AR) are the two most successful methodologies used in resolving the above-mentioned issues in HRV signals, they are specifically used to extract the power spectral information on LF and HF bands.[18] Similarly, detrended fluctuation analysis (DFA) and beat replacement, resampling, and interpolation methods have also been considered in resolving these ectopic beats in the HRV signal. Most research works concern themselves with investigating long HRV signals (> 5 min to 24 h). The same methodology will be applied in the short HRV signal collected in this research.

Major types of stress inducement stimuli named in the literature are: Stroop color word test, mental arithmetic tasks, cold presser test, and public speaking tasks.[1−3,5,7,9,12,16,20−23] More information about each type of stimulus have been given in detail.[16,25] The Stroop color word test has been widely used in many stress assessment studies to identify the effect of stress.[1,2,16,25]. This stimulus is highly capable of inducing stress in a short time within a laboratory environment, and can be associated with real-time stress.

The major objective of the investigation was to improve the stress detection rate in cardiac signals in the subject-independent mode. This paper introduces a novel methodology in terms of collection of stress inducement data from the improved stress inducement protocol, extracting and processing the ECG as well HRV signal with minimum electrodes by applying the suitable algorithm, validating the availability of powers spectral information in the short-term HRV signal using theoretical analysis as experimental result, optimizing the frequency bands and feature selection in the ECG and HRV in both of the time and frequency domains. The consideration and solving of the above issues resulted in an improved stress detection rate in both the signals in the subject-independent analysis over the 60 subjects.

The paper is organized into four sections: a brief discussion about the methods and materials used in the research to achieve our objectives, results and discussion section describing the obtained outcomes through the classification, statistical analysis and comparison of previous methods with the present findings and finally conclusion of the research.

2. Methods and Materials

2.1. *HRV signal in stress detection*

In the literature, HRV signals have been considered as a measure for identification and analysis of human stress changes.[1–10] Stress-related HRV signals were more often analyzed in a laboratory environment than in real-time. Only a handful of studies have been reported in real-time applications, such as detecting a driver's stress level,[26] and stress due to day-to-day occupational issues,[27] college examinations,[28] earthquakes,[29] and so on. Laboratory-based experiments easily evoke stress through a research protocol than real-time tasks. In laboratory-based studies, HR signals along with other physiological signals are measured frequently for stress identification. However, HRV is a more efficient signal and has more complexities involved in its analysis because it depends on how long the HR was elevated due to stress. In this kind of study, stress is usually induced within a period of a few seconds to minutes, and the stress inducement depends on the efficacy of the protocol. In this case, the major problem is due to slower HR and it is not encouraged to evaluate diagnostics purposes in various disease-based studies. However, this method can be applicable to the affective state assessment research such as stress and emotions.[13,30]

2.2. *ECG signal in stress detection*

The ECG is a well-known physiological signal that reflects the cardiac function through its unique morphological (PQRST) characteristics. In contrast to HRV signal analysis, in recent years, researchers have evinced an interest in analyzing the ECG signal more efficiently for identifying the links between emotion and stress. The majority of the meaningful information about cardiac functionality for various applications lies in between 0 and 100 Hz. Previously, in emotion research, ECG signals of 0−100 Hz and 0−10 Hz were considered in assessing the states.[31,32] ECG signals of 0−10 Hz were separated into eight equally spaced sub-bands with non-overlapping intervals to obtain a maximum mean classification accuracy of 75%

using an extended linear discriminate classifier.[31] In Ref. 32, the maximum mean classification rate of 79% and 76% is achieved using the support vector machine (SVM) and k-nearest neighbor (kNN) classifiers on distinguishing stress and the emotional states of a car driver through ECG signal of $0-100$ Hz. Usually, in HRV, the range $0-0.5$ Hz is considered to analyze the stress due to the ANS and stress relationships. In this work, the same frequency band is also blindly investigated in the ECG signal. Our previous studies also indicate that the LF range of the ECG signal is useful in detecting stress.[33,34]

2.3. *Research methodology*

The research methodology for stress assessment consisted of several steps, from stress inducement to classification. In this work, the Stroop color word test was considered to induce stress in 60 subjects (30 males and 30 females). Four physiological signals (ECG, EMG, GSR, and ST) were acquired to develop the multiple physiological signal-based stress assessment system. However, we mainly considered the cardiac signals (ECG and HRV) for improving the detection rate of more dominant signals and solve the issues in acute stress. ECG signals were acquired using a three-electrode system using AD instrument, and the acquired ECG signal was preprocessed using a wavelet denoising algorithm. Consequently, preprocessed signals were analyzed based on time and frequency domain information, in two ways: (i) extracted HRV signal from ECG signals and (ii) directly analyzing ECG using different frequency ranges. Different types of time and frequency domain features were extracted from HRV and ECG signals over different frequency ranges, and finally classified using a probabilistic neural network (PNN) and kNN. The optimum features were derived through maximum classification rate and tested using statistical validation methods. The complete research methodology is shown in Fig. 1.

2.4. *Stroop color word test*

The Stoop color word test is a well-known method to induce mental stress. It is also useful for diagnosing various cogitative functions such as selective attention, cognitive elasticity, and so on. Generally, the Stroop color word test consists of three sessions, viz., congruent, incongruent, and resting session. Complete information about the Stroop color word test can be found in our previous review.[24] In earlier researches, the protocol design and its duration differed from one to another, in the congruent and incongruent Stroop formats. Table 1 gives details about the previous studies on stress inducement protocols using Stroop color word test and relative design details.

In this work, we proposed a Stroop color word-based protocol with different time durations. This protocol consists of different levels (relaxed, low, medium, and high) to increase the mental demands gradually. A relaxation time of 3 min was given to the subjects before and after the stress inducement task. The incongruent and

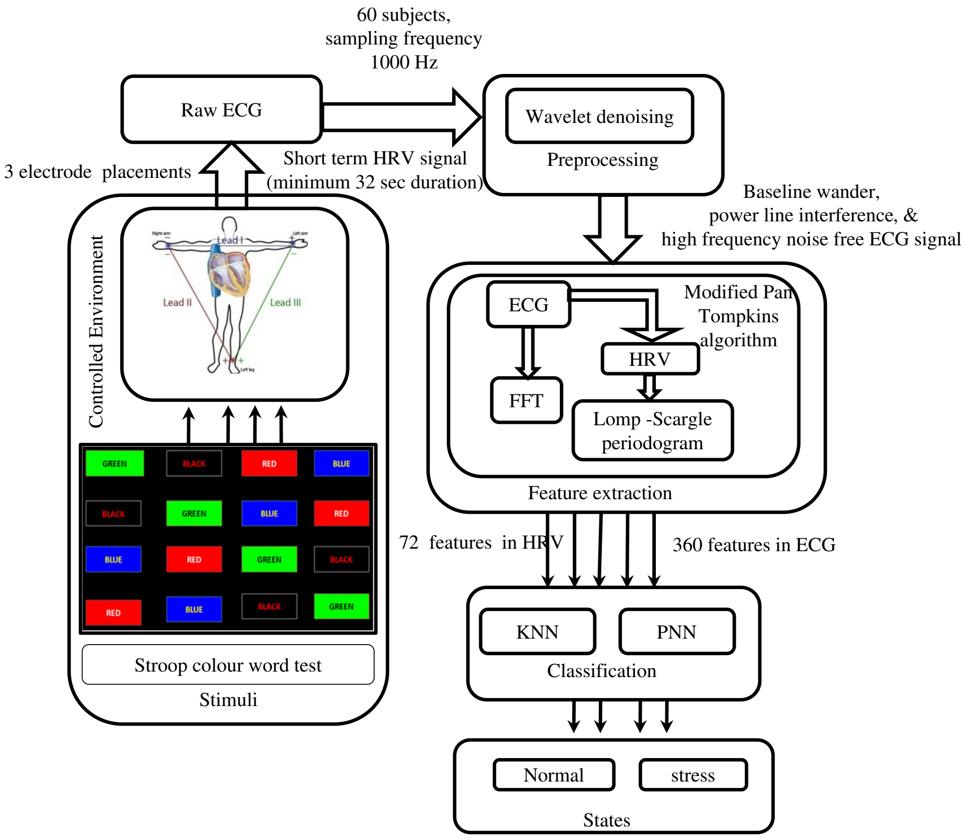


Fig. 1. Research methodology for stress detection.

Table 1. Previous works stroop color word test protocols and its duration.

References	Subject and task information	Duration	Protocol description
2	9 subjects, two sessions	20 min duration; relaxation: 20 min	Session 1 (stress session): 20 min duration of Stroop color word test. 20 min relaxation before and after the task. Session 2 (control session): Word displayed on the screen is of different color from that of the font. This session includes sound with incompatible color word on sound track to create double conflict.

Table 1. (*Continued*)

References	Subject and task information	Duration	Protocol description
24	62 subjects, Stroop color word task with other few stimuli	—	Color of word displayed incongruent with voice naming third incongruent color and voice naming some numbers on television. 1 min relaxation with 5 min task
25	45 subjects, 6 different stimuli with 8 different sets of colors with words	—	Set 1, odd sets, required to pronounce the colors (blue, green, red and yellow) Set 2, even set, subjects required to pronounce the color of letters that are significantly incongruent with color of the word.
1	38 subjects, three sessions	3 min for each session	Session 1: the font color and words written about the font color displayed differently; the subject was asked to indicate the word itself. Session 2: subject should label the color of the word. Session 3: subject should indicate the color of the word appearing simultaneously with the sound.
14	32 subjects, three sessions	each word 3 s	Session 1: 30 emotionally neutral pictures were shown. Session 2: CS, the font color and words written about the font color displayed match. Session 3: IC, the font color and words written about the font color displayed different. Session 4: resting session was considered for final relaxation.
17	106 subjects, three sessions	Stroop color word : 40 s; Relaxation: 120 s duration	Session 1 (resting session): About 120 s rest state in which the subject was relaxed with closed eyes. Session 2 (stress session (nonconflict Stroop)): About 40 s duration which has four arrangements of words: yellow in yellow ink, green in green ink, blue in blue ink and red in red ink. Session 3 (stress session (conflict Stroop)): About 40 s duration, which has four arrangements of words: yellow in blue ink red in green ink, blue in yellow ink and green in red ink.

congruent sessions were arranged in three levels (low, medium, and high) with three different time durations. The complete detailed description of the protocol is shown in Fig. 2. On the basis of the time duration, we mainly categorized the session into three groups, viz., relaxation (180 s), level 1 (low; 128 s), level 2 (medium; 64 s), and level 3 (high; 32 s). Between each level of the stress-inducement session, a duration of 20 s is given on each level to reset from pronunciation delay or fear from previous levels.

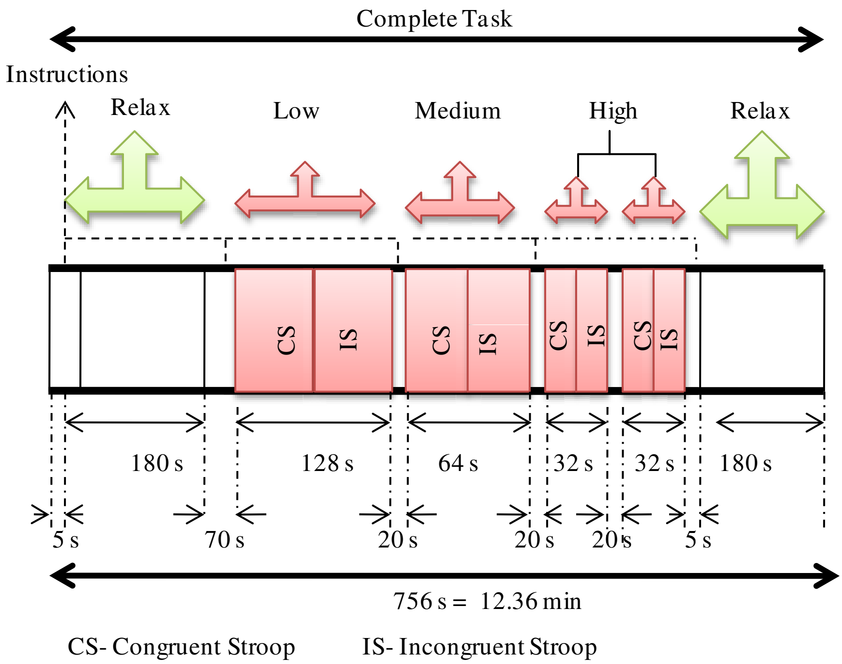
Before starting the experiment, sets of instructions were provided to the subjects about the experiment, including the following: (i) pronounce the color of the box on time, but not a written word, (ii) do not be silent during the session, (iii) increase the pronunciation speed at each level, (iv) take a deep breath, and pay attention to the music for relaxation. This complete stress-inducement protocol has been verified according to the local institutional ethical regulations. Data acquisition was carried out in a constant temperature and sound controlled laboratory environment with minimum external disturbances.

2.5. *Subjects and data*

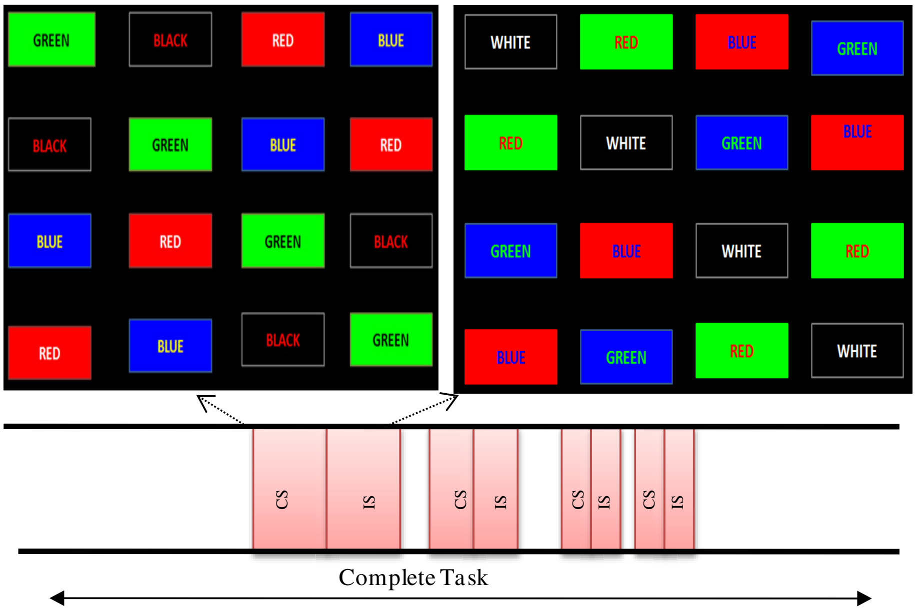
A total of 60 healthy (30 males and 30 females) subjects within the ages of 21−25 years voluntarily participated. All the subjects were non-smokers and had no previous history of medication. Before conducting the experiment, all the subjects provided informed consent, after which several questions were asked to identify their current state of health and mental condition. In addition, the objective, purpose, and protocol design of the complete experiment was explained to them. All the subjects were seated comfortably on chairs in front of a liquid crystal display (LCD) projector screen. Three ECG surface-replaceable electrodes (Ag/AgCl) were placed on the basis of an Einthoven triangle placement. The subjects were asked to relax and breathe deeply until he/she felt comfortable and relaxed, for creating the baseline data. The ECG signals were collected from the subjects during the complete experimental protocol with a sampling frequency of 1 kHz. The subjects were instructed to relax completely over a period of 30 min or, in some cases more than 30 min, depending on the subjects' comfort levels. Finally, the subjects had to report the effectiveness of the protocol after finishing the experimentation through the self-assessment form. The entire experiment was performed within controlled environmental parameters such as temperature, lighting, human interference, and sound.

2.6. *Preprocessing using wavelet denoising*

In the literature, different methods have been adopted for preprocessing the ECG signals to remove the noises, artifacts, external interferences, baseline wandering, and power line frequency interference. Most researchers so far have utilized a simple impulse infinite response (IIR) filtering for ECG signal preprocessing. However, these filters are only capable of removing the frequency of information from ECG signals which were greater than, less than or between specific cutoff frequencies. The



(a) Protocol of stroop color word test



(b) Congruent and incongruent session of stroop color word test

Fig. 2. Protocol stroop color word test.

DWT-based wavelet denoising can be applied to any kind of physiological signal without the specification of cutoff and sampling frequencies. It is a robust method which functions on the basis of the tolerable thresholding value with minimum statistically estimated risk. The selection of threshold value decides the wavelet denoising performance. The unwanted frequency bands can also be easily removed by replacing the corresponding coefficients. Our earlier works have involved different thresholding methods, rules, and wavelet function that attempted to produce ECG signals. Finally, we proved "*coif5*" wavelet, rigrsure thresholding rule, and that soft thresholding is suitable for ECG denoising.[35] Similarly, some of the previous works also made extensive use of the *coif5* wavelet function for EMG signal analysis, since it is capable of converging the signals completely in each level.[36]

2.7. *Extraction of short-term HRV signal and its power spectrum estimation in frequency domain*

Statistical features reflect the characteristics of any physiological signal. In the literature, several types of statistical features have been investigated for stress assessment through ECG signal. In recent years, the selection of optimal or more appropriate features from an entire feature set have received greater attention from several researchers. This paper explored the steps necessary to identify the appropriate feature in the ECG and HRV signals in both frequency and time domain. Figure 3 shows the detailed methods, besides listing all the features used in this work.

2.7.1. *HRV signal detection from ECG*

In 1985, Pan and Tompkins proposed that HR could be detected from an ECG signal. This ultimately led to one of the most successful algorithms ever formulated, followed by thousands of subsequent researchers in the field of HR detection. This algorithm successfully detects the HR with up to 99% sensitivity and a positive predication rate using MIT−BIH database.[37] Initially, Pan and Tompkins used low-pass and high-pass filters for identifying QRS complex in ECG signals. In recent years, bandpass filter,[38] DWT,[39] and empirical mode decomposition (EMD)[40] have also been used for improving HR detection in an ECG signal with a maximum sensitivity of 99%. In this work, the Pan−Tompkins algorithm with DWT using *coif5* mother wavelet function was used to extract QRS complex from ECG signals. Figure 4(a) shows the steps involved in using the wavelet-based Pan−Tompkins algorithm for HR detection and extraction of HRV signals deriving from an ECG signal, as given in Fig. 4(b).

In this method, the raw ECG signal is passed to the discrete derivative, moving average, and smoothing filter in order to reduce the effects of baseline wander and other noises (see Fig. 5). The filtered signal is then decomposed into eight levels in order to extract peaks of the QRS complex. The detailed coefficients (d4, d5, d6) and approximation coefficient (a4) were reconstructed after wavelet denoising,

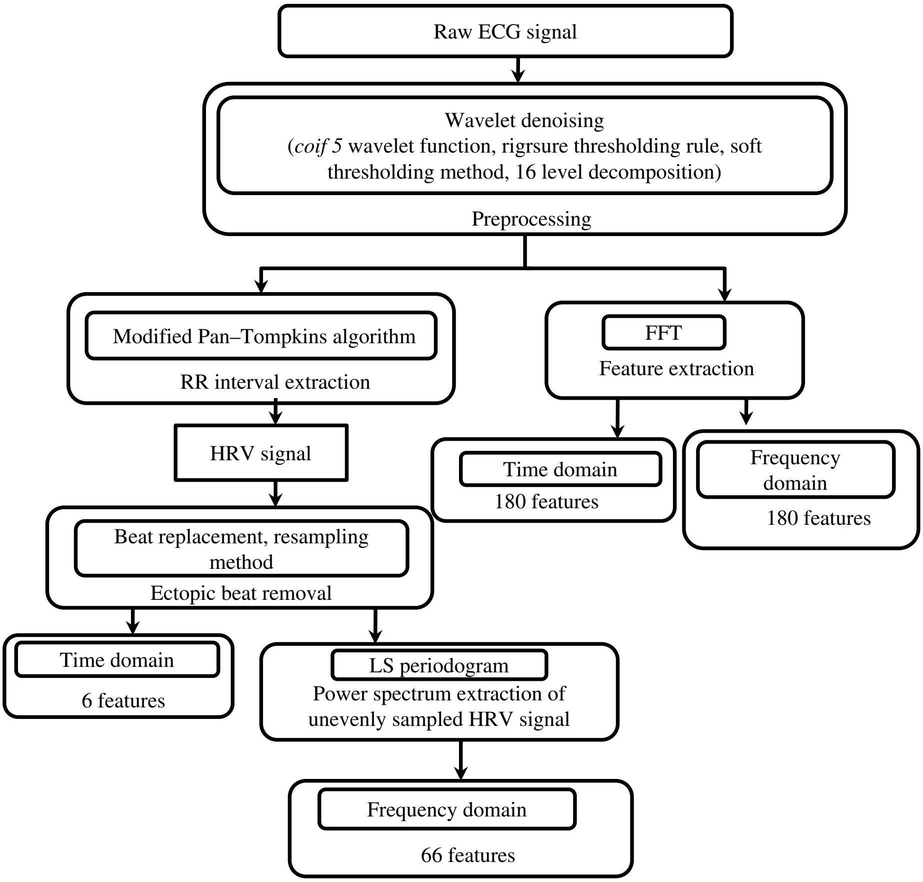
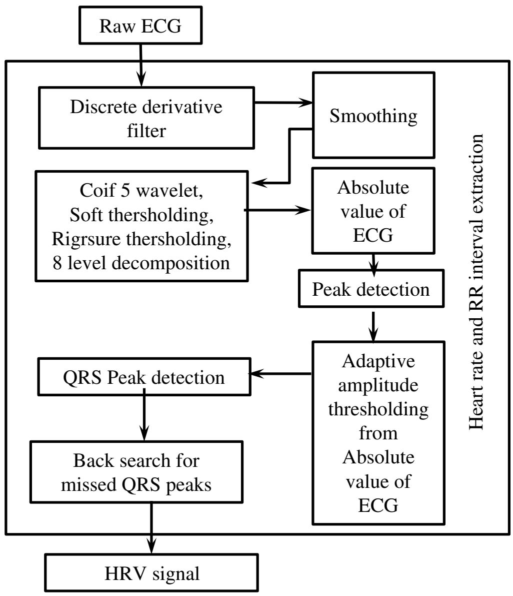
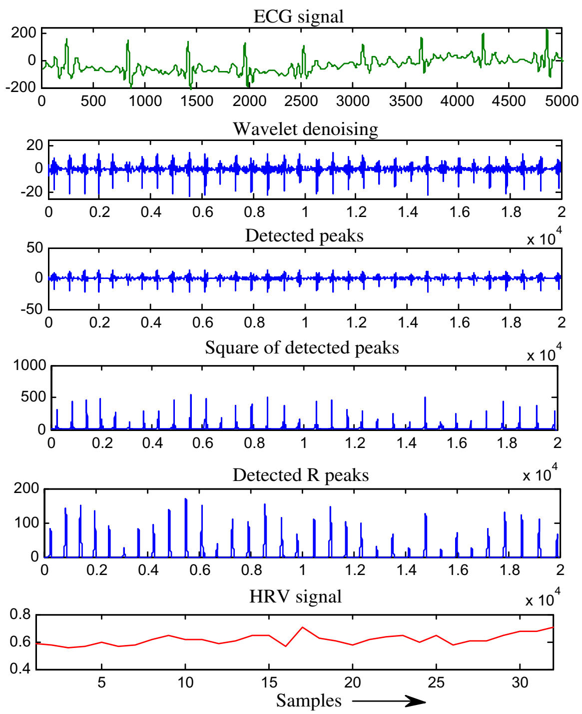


Fig. 3. Investigated features of ECG and HRV signal.

because these frequency coefficients are related to the QRS complex. In order to preserve the time information in the QRS complex, the remaining coefficients are replaced by zero. In this work, rigrsure thresholding rule and soft thresholding method were used to denoise the noises and artifacts in a QRS complex wave. Maximum and mean values of the QRS complex were calculated and subtracted, and then half the value was taken as a threshold to calculate the QRS number greater than this value. Before counting the beats, the amplitude was squared in order to count the premature ventricular beats. To extract R peak and reduce the noisy peak, the minimum and maximum beat detection duration is were set at $0.3-2$ s respectively. This is called the back search methodology for missed beats. The time duration between two RR peaks usually formed is known as the HRV signal. Figure 4(b) shows the output of the HRV signal using discrete wavelet transform based on the Pan$-$Tompkins algorithm on ECG signals. This type of HRV extraction and analysis from the ECG signal is widely used in several applications including the diagnostics of several diseases.[41]

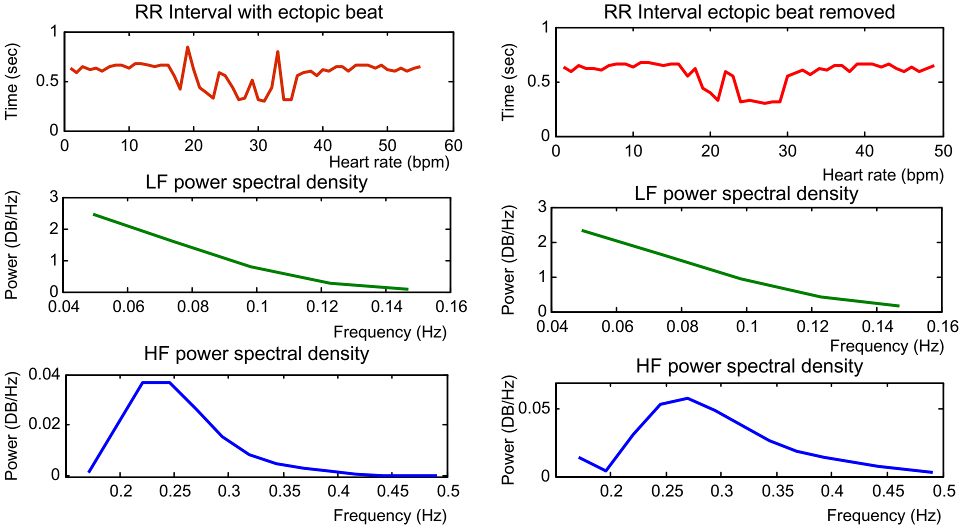


(a) HRV signal detection algorithm



(b) HRV detection in ECG

Fig. 4. HRV signal detection from ECG.



(a) HF and LF power with ectopic beat

(b) HF and LF power without ectopic beat

Fig. 5. Short-term HRV signal in ectopic beat removal.

2.7.2. *Ectopic beat removal*

The detected HRV signal was somewhat contaminated with ectopic and noise. In the literature, the time interval between two consecutive heart ($\mathrm{RR_{int}}$) beats may increase or decrease by less than 20% after QRS detection. However, if the time interval between consecutive heartbeats does not satisfy the above condition, it is called an ectopic beat. The $\mathrm{RR_{int}}$ time series can be written as:

$$\mathrm{RR_{int}} = [t_1, t_2, t_3, \ldots, t_n], \tag{1}$$

where t_1, t_2 are the first and RR interval duration in RR interval time series. To satisfy the above conditions, the above equation can be rewritten as

$$\begin{aligned}\mathrm{RR_{int}} = [&t_1, 0.8t_1 \leq t_2 \geq 1.2t_1, 0.8t_2 \leq t_3 \geq 1.2t_2, 0.8t_3 \leq t_4 \geq 1.2t_3, \ldots, \\ &0.8t_{n-1} \leq t_n \geq 1.2t_{n-1}].\end{aligned} \tag{2}$$

The presence of ectopic beat introduces the HF and LF components, because the time duration is considered as the magnitude which is directly proportional to the amplitude and frequency of the HRV time series. Further, the unsatisfied condition creates the irregular power spectral estimations. In order to resolve this issue, a beat replacement, artificial RR generation, interpolation, and resampling comprises the alternate method incorporated for the time duration greater than 5 min.[18] Similarly, DFAs were frequently used for ectopic beat removal.[42,43] In this work, the beat replacement, artificial RR generation, interpolation, and resampling method were employed for the duration of 32 s. The following information will represents the

Table 2. Statistical information with and without ectopic beat in short-term HRV signal.

Band	Feature	Ectopic beat	After ectopic beat removal
LF	Min	0.131	0.050
	Max	2.330	2.474
	Mean	1.092	1.032
	Median	0.945	0.786
	Mode	0.131	0.050
	Std	0.894	0.996
	Range	2.199	2.424
HF	Min	0.003	0.000
	Max	0.058	0.037
	Mean	0.024	0.011
	Median	0.016	0.004
	Mode	0.003	0.00001
	Std	0.019	0.014
	Range	0.054	0.037

feasibility of analyzing short-term HRV signals.

$$\mathrm{RR}_{\mathrm{interval}} = (t_1 = t_1), (t_2 = 0.3t_1), (t_3 = 0.8t_1), \ldots, (t_n = \tau * t_1), \tag{3}$$

where τ is the time factor corresponding to the first beat. The ectopic beat (t_2) in the time series can be placed by the phantom beat ${t_2}^1 = (t_3 - (t_1)/2$.[18] This phantom beat is sometimes called interpolation. The power spectral variation in HF and LF bands was found to be significantly changed after the replacement of ectopic beats. Figures 5(a) and 5(b) show the effects of ectopic beat and methods for its removal, for QRS detection in ECG signal. Table 2 presents the statistical feature values of LF and HF bands before and after ectopic beat removal.

2.8. *Hypotheses of HRV signals at different durations*

In general, HR (interval between consecutive R peaks) detection from QRS wave is not consistent, it is a purely subjective. Previously, 7-Hz resampling could analyze up to 210 bpm.[18] Table 3 presents the sampling frequency distribution for different HRs. We extracted the different probabilities and its time durations for better enhancement.

Table 3. Sampling frequency distribution of all range of HRV signals.

Heart rate (bpm)	Sampling frequency (Fs) in Hz = (number of beats per min*2)	Ts = 2*(1/Fs) s/sample
210	(210/60)*2 = 6.9	0.14
120	(120/60)*2 = 4	0.25
60	(60/60)*2 = 2	0.5
30	(30/60)*2 =1	1

Notes: Ts: Sampling time; bpm: beats per minute.

Table 4. Minimum time duration to analyze the LF and HF bands in HRV signal.

Duration (sec)	Frequency limit (Hz)	Significance
300	(1/(60*300) = 0.003	Above the VLF region
60	(1/60*60) = 0.016	
30	(1/(60*(32/60)) = 0.031	
25	25 s = (1/(60*(25/60)) = 0.04	LF region starts, VLF completely lost
20	20 s = (1/(60*(20/60)) = 0.05	LF lost and HF information only retained

According to European and North American Task Force standards, the minimum time required for HRV metrics assessment is 5 min,[14] which allows the lower frequency of up to 0.003 Hz (1/(60*5) = 0.003 Hz). However, if the duration of HRV less than 5 min duration exists (e.g., emotion and stress studies), the minimum possible time required to compute the HF and LF bands from HRV signal as per the same principle, is given in Table 4.

In order to obtain the minimum frequency limit on HRV signal analysis, 25 s will be the optimum, as any duration less than this frequency range results in loss of the LF bands. Hence, a duration of less than 25 s will not be suitable for time and frequency domain analyses in HRV signals.

Note that the ANS activity related to HRV lies between 0.04 and 0.5 Hz. Therefore, minimum power spectral analysis of ANS can be done if the analysis window is greater than 25 s duration, and the minimum and maximum values of HR lie between 210 and 48 bpm. Consequently, the corresponding sampling frequency limits tend toward 7.14−1.6 Hz (see Table 5). However, the limited numbers of magnitudes of the frequency ranges were only available for this short time duration. Further, the identification of accurate sampling frequency was a major issue in this analysis. It is, therefore, essential to discuss the most suitable method for deriving the frequency and power spectral estimation from unevenly sampled signals.

Table 5. Short-term HRV and number of beats related to HF and LF band.

Heart rate (bpm)	RR_{int} duration = (60\Number of beats) (s)	No of RR_{int} per sec (beats)	Minimum and maximum possible range of single RR_{int} (s)	Minimum and maximum of samples for 25 s HR_{32} (beats)	Sampling frequency range of HRV (Hz)
240	60/240 = 0.25	1/0.25 = 4	$0.28 \leq RR_{int} \geq 1.25$	25*3.57 = 89	3.57*2 = 7.14
210	60/210 = 0.28	1/0.28 = 3.57		25*0.8 = 20	0.8*2 = 1.6
48	60/48 = 1.25	1/1.25 = 0.8		$089 \leq HR_{32} \geq 20$	$7.14 < Fs > 1.6$
30	60/30 = 2	1/2 = 0.5			

Notes: $HR_{32-\text{heart rate for the 32 s.}}$

2.8.1. *Evenly sampled HRV signal and its extraction of signal power using FFT*

In general, consider a physical model, which consists of physical variable X, with the random observational error (R) is measured at the time of t_j. Thus, the corresponding time series can be written as

$$X_j = X(t_j) + R(t_j), \tag{4}$$

where $j = 1, 2, 3, \ldots, n$, and n is the dimension of time series. Furthermore, more evenly sampled signals are periodic and errors are independent with respect to time. In this $R(t_j)$ is zero, which means that it has constant variance.

Similarly, the $\mathrm{RR_{int}}$ of HRV signal is expressed as

$$\mathrm{RR_{int}} = [t_1, t_2, t_3, \ldots, t_n]. \tag{5}$$

In the case of a uniform HRV signal,

$$\mathrm{RR_{int}} = t_1 = t_2 = \cdots = t_n. \tag{6}$$

In detail, sampling in equal time can be rewritten as $\Delta t = t_{j+1} - t_j = \text{constant}$, where j is the jth sample of $\mathrm{RR_{int}}$ time series. Therefore, the HRV is in perfect periodic timing:

$$\mathrm{HRV} = X(t_j) = \left[\frac{60}{\Delta t}, \frac{60}{\Delta t}, \ldots, \frac{60}{\Delta t}\right], \text{bpm}. \tag{7}$$

Thus, the fundamental frequency of HR can be represented by $\omega_0 = \frac{2\pi}{\Delta T}$. Here, the random observational error (R) also tends to zero. In order to compute the power values from the signal, FFT is incorporated.

The discrete Fourier transform of the sequences is represented as N points

$$\mathrm{FT}_X(\omega) = \sum_{j=0}^{N-1} X(t_j)\mathrm{e}^{-iw_n t_j}, \tag{8}$$

where $w_n = 2\pi f_n$ and $n = 1, 2, 3, \ldots, N$, and $i = \sqrt{-1}$.

Therefore, the power spectral density $X(t)$ of periodically sampled signal is calculated as

$$P_X(\omega) = \frac{1}{N}\sum_{J=0}^{N-1} |X(t_j)\mathrm{e}^{-iw_n t_j}|^2. \tag{9}$$

Normally, this method is applicable when the input signal is in an ideal state, and is not suitable for a constantly varying signal.

2.8.2. *Unevenly sampling HRV and its signal power estimation using LSP*

Practically, in real time, the HR is not uniform, and depends purely on time, that is, $T \neq t_1 \neq t_2 \neq \cdots \neq t_n$.

So, the HRV signal is rewritten as

$$\text{HRV} = X(t_j) = \left[\frac{60}{t_1}, \frac{60}{t_2}, \ldots, \frac{60}{t_n}\right]^T, \text{bpm}. \tag{10}$$

Here, the random observational error (R) does not tend to zero, and has some mean value and variance.

$\Delta t \neq t_{j+1} - t_j \neq$ constant. The simplification of uneven sampled complex signal ($t_1 \neq t_2$) is computed by using N-point DFT with random t_j.

$$F : T_x(\omega) = \left(\frac{1}{N}\right)^{\frac{1}{2}} \sum_{j=0}^{N-1} X(t_j)[P\cos(wt_j) - iQ\sin(wt_j)], \tag{11}$$

where P and Q are unspecified functions of angular frequency ω, j is the summation index, and w is the dependent variable of sample time (t_j), but not data $X(t_j)$. The corresponding normalized periodagram is

$$\begin{aligned} P_X(\omega) &= \frac{1}{N}|FT_X(w)|^2 \\ &= \frac{P^2}{2}\left[\sum_j X(t_j)\cos(wt_j)\right]^2 + \frac{Q^2}{2}\left[\sum_j X(t_j)\sin(wt_j)\right]^2, \end{aligned} \tag{12}$$

where $P = Q = (\frac{2}{N})^{\frac{1}{2}}$, here $\mathrm{FT_X}$ reduces to the DFT. Then, the limits of Δt tends to 0 and N tends to ∞. This equation is not a unique expression. This is imposed by Scargle using the following periodogram method, namely LSP.[44] Later on, Glifford applied this LSP to HRV signal studies.[18]

The power in this kind of complex equation was corrected and called as LSP.[18]

$$PN(\omega) \equiv \frac{1}{2^{\sigma 2}}\left\{\frac{[\sum_j (x_j - x)\cos(\omega(t_j - \tau))]}{\sum_j \cos^2(\omega(t_j - \tau))} + \frac{[\sum_j (x_j - x)\sin(\omega(t_j - \tau))]^2}{\sum_j \sin^2(\omega(t_j - \tau))}\right\}^2, \tag{13}$$

where $\mathrm{PN}(\omega)$ allows into independent shifting of all the t_j by any constant, where, $\tau \equiv \tan^{-1}\left(\frac{\sum_j \sin(2\omega t_j)}{\sum_\mathrm{j} \cos(2\omega t_j)}\right)$, the mathematical equation was used from the previous works of Carry, and further information can be obtained in Ref. 18. Here, the sampling frequency is decided by the minimum $\mathrm{RR_{int}}$ HRV signal without any artifacts and ectopic beats. The following results explored the presence of $\mathrm{RR_{int}}$ and the corresponding HF and LF spectra of HRV signal, when the time duration is 32 s, by using our stress assessment data.

2.9. *Features of HRV*

In this work, a set of statistical and geometrical measures were derived from the HRV signals in time domain. The statistical measures are: standard deviation of

RR_{int} (SDNN), standard error RR_{int} (SENN), root mean square deviation, successive difference of RR_{int} (RMSSD) and standard deviation of adjacent RR_{int} (SDNN). The total number of RR_{int} differed from 50 ms in the entire recording (NN50), and NN50 divided by total of RR_{int} in percentage (PNN50) was used in this work.[14] In a similar approach, the geometrical features, viz., triangular index of RR_{int} (TINN), differential index and logarithmic index, are significant parameters considered for HRV signal analysis.[14,17] In this work, HR, mean RR_{int}, NN50, PNN50, Power, RMMSD, and (TINN) were analyzed in the time domain (see Table 6). TINN is widely used in long-term HRV signals that are greater than 24-h data. Though long-term HRV signals are highly sensitive to noise and artifacts, we tried to incorporate this feature in this work for identifying the effectiveness of this feature in short-term HRV analysis.

In frequency domain analysis, if the HRV signal duration is greater than 5 min, it means the average power in HF and LF bands is most analyzed, as given in the literature. In this work, LF (0.04−0.15) Hz, HF (0.04−0.15), (HF + LF) = TF (0.04−0.5) Hz band power distribution and LF/HF, LF/TF, and HF/TF ratio are considered as inputs to derive the following statistical features: standard deviation, mean (μ), covariance (Cov), second-order cumulant (k_2) third-order cumulant (k_3), fourth-order cumulant (k_4), kurtosis (γ_k), skewness (γ_s), energy, power, entropy, minimum and maximum values of power for classifying the stress levels (see Table 6).

The higher-order statistics (HOS) parameters (second-order cumulant (k_2) third-order cumulant (k_3), fourth-order cumulant (k_4), kurtosis (γ_k), skewness (γ_s)) were very suitable for any signal which exhibited non-linear, non-stationary and non-Gaussianity distribution in nature.[45] Hence, it is applicable to HRV signal, and with added advantages of second-order correlations and power spectrum of HRV signals. Previously, seven classes of arrhythmia were studied using HOS in HRV signals.[46] Skewness quantifies the asymmetric distribution and, therefore, sudden acceleration and slowly decelerating condition in clinical application was investigated.[47] Similarly, Kurtosis describes flat or peak distribution in any data. Table 6 indicates the computation of various features analyzed in both time and frequency domain analyses.

2.10. *Features of ECG*

The ECG (0−100) Hz has cleaved into different frequency ranges, (0−10) Hz, (0.04−0.14) Hz, and (0.14−0.5) Hz. About (0−10) Hz is equally cleaved into eight non-overlapping frequency ranges based on the emotion in previous works in the emotion classification study.[31] Similar features of the HRV frequency domain were considered for investigating the time and frequency domain of ECG signals. In addition, first-order difference (FOD), RMS, energy, entropy, and covariance were also computed,[34] but, the amplitude spectrum was investigated, rather than the power value of HRV.

Table 6. Computation of statistical features.

S. No	Feature	Formula	Description and remarks
1	First-order difference	$\mathrm{FOD} = \sum_{j=1}^{n}(x_j - x_{j+1}) + (x_{j+1} - x_{j+2}) \ldots (x_{n-1} - x_n)$	x_j is the jth sample of any time series n is the number of observations.
2	Mean (μ) (first moment)	$\mu = \sum_{j1}^{n} \frac{(x_j + x_{j+1} + \cdots + x_n)}{n}$	Mean is called as first moment, which is defined as the ratio of sum of variables divided by total variables.
3	NN50	$\mathrm{NN50} = (x_j - x_{j+1} > .05), (x_{j+1} - x_{j+2} > .05) \ldots (x_{n-1} - x_n > .05)$	Total number of $\mathrm{RR_{int}}$ is differing from 50 ms in the entire recording.
4	PNN50	$\mathrm{PNN}_{50\,=}\,\mathrm{NN}_{50\,/}$ total of $\mathrm{RR_{int}}$	Ratio of $\mathrm{NN_{50}}$ to the total value of $\mathrm{RR_{int}}$.
5	RMSSD	$\sqrt{\frac{1}{n-1}\left(\sum_{j=1}^{n-1}((x_{j+1} - x_j) + \cdots + (x_n - x_{n-1}))\right)^2}$	RMSS returns the successive differences being neighboring variables.
6	HRV triangular index	$\mathrm{HRV_{TI}}$ = total number of $\mathrm{RR_{int}}$/ height of histogram of all $\mathrm{RR_{int}}$	Geometrical feature $\mathrm{HRV_{TI}}$ returns the ratio between total number of $\mathrm{RR_{int}}$ and height of histogram of all $\mathrm{RR_{int}}$.
7	Energy	$E = \sum_{j=1}^{N}(x_j^2 + x_{j+1}^2 + \cdots + x_n^2)$	Squaring the signal or taking its absolute value, then finding the area under that curve returns energy of the signal.
8	Power	$P = \sum_{j=1}^{n} \frac{(x_j^2 + x_j^2 + \cdots + x_n^2)}{n}$	Power is a time average of energy
9	Second cumulant	$k_2 = \frac{1}{n}\sum_{j=1}^{n}(x_i - \bar{x})^2$	
10	Third cumulant	$k_3 = \frac{1}{n}\sum_{j=1}^{n}(x_i - \bar{x})^3$	Higher-order spectral analysis
11	Fourth cumulant	$k_4 = \frac{1}{n}\sum_{j=1}^{n}(x_i - \bar{x})^4$	

Table 6. (*Continued*)

S. No	Feature	Formula	Description and remarks
12	Kurtosis (fourth moment)	$\gamma_k = \frac{k_4}{k_2^2} = \frac{\frac{1}{n}\sum_{j=1}^{n}(x_i-\bar{x})^4}{\left[\frac{1}{n}\sum_{j=1}^{n}(x_i-\bar{x})^2\right]^2}$	Kurtosis is more commonly defined as the fourth cumulant divided by the square of the second cumulant. $\bar{x}$ sample mean,
13	Skewness (fourth moment)	$\gamma_s = E\left[\left(\frac{x-\mu}{\sigma}\right)^3\right] = \frac{k_3}{k_2^{1.5}} = \frac{\frac{1}{n}\sum_{j=1}^{n}(x_i-\bar{x})^3}{\left[\frac{1}{n}\sum_{j=1}^{n}(x_i-\bar{x})^3\right]^{3/2}}$	Ratio of the third cumulant $\kappa 3$ and the 1.5th power of the second cumulant $\kappa 2$.
14	Root Mean Square Value (RMS)	$\mathrm{RMS} = \sqrt{\frac{(x_1^2+x_2^2 \cdots x_n^2)}{n}}$	Root of square of each sum of variable divided by total variables
15	Co-variance(cov)	$\mathrm{Cov}(x) = E[(x_1-\mu)\ldots(x_n-\mu)]$	E is the mathematical expectation and
16	Entropy	$H = -\sum_{i=1}^{n} p(x_i)\log_{10}p(x_i)$	where, $x = (x_1, x_2 \ldots x_n)$ is a set of random phenomena of wavelet coefficient, and p is a probability of random phenomenon of wavelet coefficient.

2.11. *Classification*

2.11.1. *kNN*

kNN is the simplest type of classifier, and is used to discriminate unknown or complex distribution feature values in feature space.[48] The maximum accuracy in the minimum value of k shows the best discrimination of data. Maximum k value indicates that the boundaries are smooth. Several types of distance measures are used in kNN classifiers for calculating the distance between the unknown data from the groups, such as: Euclidian, city block, and cosine. More often, the Euclidian distance rules are extensively proved to be the best discrimination of data by using the following function in Eq. (14).

$$d(x,y) = \|x-y\| = \sqrt{(x-y).(x-y)} = \left(\sum_{i=1}^{m}(x_i-y_i)^2\right)^{1/2}. \tag{14}$$

2.11.2. *PNN*

PNN, first proposed in 1990, works based on the probability density function (PDF).[49] PDF is computed by using Bayesian classifications and classical estimators. In order to discriminate the features in N classes, the following PDFs are used in Eq. (15). PNN has input, pattern, summation, and output layers. The entire input unit is interrelated, and activation of the pattern unit is usually done by using a sigmoid function. The function of pattern unit calculates the distance from input of the training vectors whose elements are closer to the groups. Similarly, the function of the summation unit sums each class of contributions

$$f_i(x) = \frac{1}{(2\pi)^{p/2}\sigma^p m_i}\sum_{k=1}^{m_i}\exp\left[-\frac{(x-x_{ik})^T}{2\sigma^2}\right], \tag{15}$$

where the testing input x_{1i} is the training pattern from 1, m_i is the dimension of ith population, p is the dimension of input vector and σ is the standard deviation of the Gaussian distribution. $f_1(x) > f_j(x)$, all $j \neq k$, $f_i(x) = \frac{1}{n_i}\sum_{k=1}^{n_i} \mathrm{e}^{-\frac{|x-x_{ik}|^2}{\sigma^2}}$ is eliminated from the common factors, and absorbed into the 2σ. The large value of this σ determines the position of the hyper plane, and smaller values indicate the nonlinear decision boundaries. In this work, σ value has been changed from 0.01 to 0.1 in 10 equally spaced intervals.

3. Results and Discussion

The main purpose of this study was to test whether relevant information relating to stress can be identified during stress-inducing stimuli using ECG signal and short-term HRV signals. Initially, a total of 432 features were computed in both HRV and ECG signals. In ECG signals, 360 (15 frequency bands* (12 features in time domain and 12 features in frequency domain)), and in HRV 72 features (6 time domain features, 3*11 frequency band features, 3*11 frequency band ratio), the true positive (TP), false positive (FP), true negative (TP) and false negative (FN) were calculated in each feature in order to describe the performance by measuring sensitivity, specificity, and overall accuracy.

$$\begin{aligned} \text{Sensitivity} &= \text{TP}/(\text{TP}+\text{FN}), \\ \text{Specificity} &= \text{TN}/(\text{TN}+\text{FP}), \quad \text{and} \\ \text{Overall accuracy} &= \text{TP}+\text{TN}/(\text{TP}+\text{TN}+\text{FP}+\text{FN}), \end{aligned}$$

where TN is the classifier discriminated as normal when the normal sample presents, TP is the classifier discriminated as stress when the stress sample presents, FP is the classifier discriminated as stress when the normal sample presents, and FN is the classifier discriminated as normal when the stress sample presents.

3.1. *Classification result of HRV*

The stress-detection rates in percentages have been insufficiently reported using the HRV signalor any other physiological signals in stress-assessment studies. Previously, Healy *et al.*, and Zhai *et al.*, have reported detection rates in percentages in their research which is a highly subject-dependent study using multiple physiological signals.[10,26] Individual efficacy on each signal was not reported in those studies. On the basis of the accuracy, results are only capable of indicating the reliability of each signal. Here, in this study we proceeded with the intention to report the single signal and its dominating features results more elaborately. A relaxed state is considered as normal, and high level is considered stress. Out of 72 heart features, the HOS feature, namely third-order cumulant, produces the best classification accuracy in the frequency range of 0.04−0.5 Hz. The results of PNN, conventional, and 10-fold cross-validation of kNN is shown in Table 7.

Table 7. Classification results of some of the HRV signal features in all the classifiers.

Domain	Band	Features	Classifier	K value/ Spread factor	Sensitivity	Specificity	Overall accuracy
Freq.	TF	3rd cumulant	kNN CONV	2	91.67	91.67	91.67
	TF	4th cumulant		1	88.24	84.21	86.11
	LF	Power		3	93.33	80.95	86.11
Time	–	Heart rate		1	60	57.14	58.33
Freq.	HF	Power		6	88.24	84.21	86.11
Time	–	NN50	K-FOLD	9	91.11	74.67	80.83
Freq.	TF	3rd cumulant		1	94.12	89.47	91.67
	HF	4th cumulant		10	79.25	73.13	75.83
	HF	Kurtosis		9	83.33	77.27	80
Freq.	TF	3rd cumulant	PNN	0.1	90.91	84.62	87.5
	LF	Skewness		8	70	75	72.22
	HF	Skewness		0.1	80	87.5	83.33
	HF	Kurtosis		1	80	87.5	83.33

Notes: Freq. - frequency, TF − 0.04−0.5 Hz, kNN CONV- kNN conventional classifier, K-FOLD- kNN 10-fold cross validation.

When the k value is minimized, kNN performs well, and the overall classification accuracy is changed from 86.67% to 91.67% when using the k values up to 10. The maximum accuracy in conventional kNN is 91.67%, which reflects achieving a sensitivity and specificity of 91.67%. Similarly, in the k-fold kNN, the overall accuracy is 91.67% when the k value is 1. Table 7 shows the PNN-based classification result of the same features used in kNN. Here, we were different spread factors like kNN k value. In this study, when the spread factor value was at the minimum, the classification rate was very high, but the spread factor should be at maximum as far as possible, Since, we increased the spread factor from 0.01 to 0.1, which resulted in the reduction of accuracy from 91.67% to 83.33%. In PNN, we obtained the maximum overall classification accuracy of 91.67% when the spread factor was 0.01. There was no improvement or change in accuracy when the spread factor was increased up to 0.1.

3.2. *Classification result of ECG*

In an earlier discussion, we mentioned that ECG during stress and emotions had been rarely studied. This is the blind investigation that predicates some correlation over the different frequency bands with different features of stress states in all the subjects who participated. Table 8 shows the various features dominant in an ECG signal-based stress assessment. However, our proposed study correlates with the existing ECG-based emotion study frequency ranges with improved classification in this work.

The various 1−10 k values were tested in both conventional and 10-fold cross-validation. The maximum classification accuracy was achieved in 94.44% in conventional kNN when the k value was 4. Similarly, the maximum overall classification accuracy was obtained in 94.17% in k-fold cross-validation. Another notable

Table 8. Classification results of some of the ECG signal features in all classifiers.

Domain	Band (Hz)	Feature	Classifier	K value/ Spread factor	Sensitivity	Specificity	Overall accuracy
Freq.	(0.04−0.5)	RMS	kNN CONV	10	78.57	68.18	72.22
	(0−1.25)	Mean		3	100.00	90.00	94.44
	(0−10)	Energy		3	86.67	76.19	80.56
Time	(0−1.25)	Entropy		5	75.00	70.00	72.22
Freq.	(0−1.25)	RMS	K-FOLD	8	88.64	72.37	78.33
	(0−10)	Energy		5	94.34	85.07	89.17
	(0.04−0.5)	RMS		9	79.69	83.93	81.67
	(0−1.25)	Mean		3	96.49	92.06	94.17
Time	(0−1.25)	Entropy		8	77.78	72.73	75.00
Freq.	(0.04−0.5)	FOD	PNN	1.00	100.00	75.00	83.33
	(0.04−0.5)	Entropy		0.40	86.67	76.19	80.56
	(0.04−0.5)	RMS		0.10	100.00	75.00	83.33
	(0−1.25)	Mean		0.10	88.89	100.00	93.75
Time	(0−1.25)	Entropy		0.10	76.47	73.68	75.00

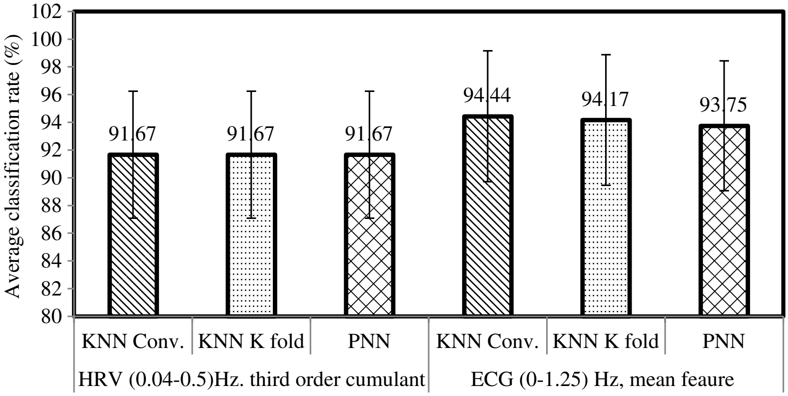


Fig. 6. Overall classification rates of all the classifiers in short-term HRV and ECG under normal and stress state.

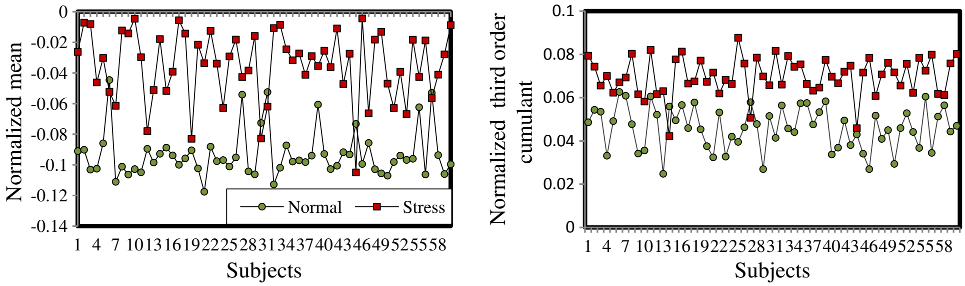
finding was that even when we changed the various k values, the accuracy did not fall to less than 90% in both classifiers. To verify these results, the PNN was also tested with various spread factors. The result indicated improved classification accuracy when the spread value was very low (0.01). Usually, the maximum spread factor is better than the minimum spread value; when we increased the spread value, it reduced up to 93.75%. However, in this work, the spread factor was not seen to be more effective beyond a certain value. Figure 6 shows the maximum overall classification results of the dominant features in the two signals.

3.3. *Statistical analysis of dominant ECG and HRV features*

On the basis of the results, the following two features dominant were considered for statistical analysis using one-way ANOVAs. The HOS of HRV features (normalized third-order cumulant), between normal and stress F (1,119) = 11.38, $p < 0.001$, in normal state ($M = 0.046$, SD = -0.0097), and in stress ($M = 0.069$, SD = -0.0087) shows statistically significant. Similarly, the mean feature of ECG between normal and stress F (1,119) = 16.24, $p < 0.001$, in normal ($M = -0.093$, SD $-$ 0.015), and in stress ($M = -0.034$, SD = -0.022). The result indicated the significance of both the features for the classification of normal over stress. Figure 7 shows the normalized feature vector of each subject which was elevated from normal to stress states in HRV while analyzing the third-order cumulant feature. Similarly, when we analyzed the third-order cumulant of power spectrum of $0.04{-}0.5$ Hz, the normalized mean value of $0{-}1.25$ Hz significantly increased from normal to stress state.

3.4. *Comparisons of previous stress research*

The Stroop color word-based stress improved stress inducement protocol, wavelet-based preprocessing, FFT- and LSP-based feature extraction, various time and



(a) HRV feature

(b) ECG feature

Fig. 7. Dominant features elevation in normal and stress.

frequency domain-based feature selection and simple nonlinear classifier namely kNN and PNN are the major steps helpful to improve the stress detection rate. Table 9 compares previous studies investigating stress detection using classifier or statistical analysis. The majority of previous works did not concentrate in the deepth on studying signal processing methods especially noise removal and feature extraction methods and features. On the other hand, in most previous works subject dependent analysis,[1,2,10,16,26,50] had a very small population of subjects. The maximum classification accuracy of 97% was obtained by investigating the stress levels of 22 drivers in the highly subject-dependent analysis using video metrics as well as questionnaires.[26] The Stroop color word test-based stress detection was performed, achieving a maximum classification accuracy of 90.02% in the subject-dependent analysis, which is the most similar work compared our research. The examination of stress was investigated and the classification of accuracy of 90% was obtained using the HRV signal in subject-dependent analysis and manual correction HRV signal detection with 48 subjects. This work has been outperformed in terms of subjects, classification rate, distinct features with the classification accuracy of 91.67% and 94.44% in HRV and ECG signals, respectively.

Table 9. Comparison of previous works related stress detection.

References	Protocol & Data analysis	Number of subjects	Physiological signals and list of statistical features	Remarks
Present work	Strop color word test & Subject independent study	60	ECG & HRV (472 features in different frequency bands and ratios)	kNN classifier produces the result of 94.44% and 91.67%. PNN classifier produces the result of 93.75% and 91.67%

Table 9. (*Continued*)

References	Protocol & Data analysis	Number of subjects	Physiological signals and list of statistical features	Remarks
Present work	Strop color word test & Subject independent study	60	ECG & HRV (472 features in different frequency bands and ratios)	kNN classifier produces the result of 94.44% and 91.67%. PNN classifier produces the result of 93.75% and 91.67%
10	Stroop color word test & Subject dependent study	32	ECG, GSR, Blood Volume Pulse, Pupil Diameter and Skin Temperature (11 Features).	SVM (90.10%). Decision Tree classifier (88.02%) Naïve Bayes classifier (78.65%)
1	Stroop color word test & Subject dependent study	38	Heart Rate (HR) and BP	Classifier not involved. HR and BP are strongly correlated with stress.
17	Stroop color word test & Subject dependent study	106	Electro dermal Response (EDA)	Classifier not involved. EDA increased during the stressful task
2	Stroop color word test & Subject dependent study	9	ECG, EDA, EMG and RR	All four signals are showing significant changes during the stress

4. Conclusion

HRV and ECG have been used for measuring stress due to being less invasion and a direct reflection of ANS corresponding to stress. However, the duration of HRV might be a problem for this analysis of ANS activity related to stress. The proposed novel methodology was incorporated and its feasibility tested. In order to optimize the stress-related features, various time and frequency domain of HRV and ECG were investigated and the results of more dominant features were reported. Third-order cumulant in 0.04−0.5 Hz of HRV and a mean of 0−1.25 Hz of ECG features gave a better discrimination between normal and stress states even in the subject-independent studies using short-term (32 s) signals. The descriptive statistical analysis and classification results strongly suggest that the short HRV signal (>32 s) can be used for analysing ANS by applying a more potent algorithm incorporated in this work. The validated methods will be helpful in the consideration of short-term HRV signal in affective computing research such as stress level detection, emotion classification, drowsiness detection, etc. The obtained results showed that the overall stress detection rate had been improved in the subject-independent mode compared to previous subject-dependent studies with the least number of subjects. Additionally, the hypothesis suggested that the HRV signal can be used if we collected greater than 25 s for affective assessment researches. However, the HRV signal in between 25 s to 5 min is very sensitive to noise and ectopic beats due to the limited frequency pins. In the future, the optimized features of the ECG and HRV signals will be combined with the optimized features in other physiological signal features (EMG, GSR, and ST). The reliability of the system will be improved by fusing such efficient features coming from different sensor. This multiple evidence-based stress detection will offer global decision about stress and its levels.

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