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Prediction of Drowsy Drivers Fault Using Bio Signals Joint Stachostic FSD (BJSFSD) Algorithm

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Abstract: In this article, we propose a novel approach to recognize emotions with the help of privileged information, which is only available during training, but not available during testing. Such additional information can be exploited during training to construct a better classifier. Specifically, we recognize audience's emotion from EEG signals with the help of the stimulus videos and tag videos' emotions with the aid of electroencephalogram (EEG) signals. Proposed work consists of Multi modal(EEG,ECG,PPGand video frames) bio signal for drowsy level detection which are sensed by the sensor module (sensing). Then the proposed BJSFSD algorithm used to analyse the bio signal processing module. The sensing module senses ECG signals via conductance fabric and senses PPG signals via the driver's finger. all the EEG,ECG and PPG sensors are attached to the steering wheel; thus, body attachment is not required. As we mentioned earlier video camera is fixed to capture the driver eye blink and face detection. First, frequency features are extracted from EEG signals and audio/visual features are extracted from video stimulus. Second, features are selected by FSD statistical tests. The proposed methods thus might be practicable for applying to an online portable embedded system to perform a real-time alertness monitoring system. The system employs behavioral, physiological and vehicle based methods to determine if a driver is alert or not.

Key words: PPG sensors · EEG signals · BJSFSD algorithm · FSD statistical tests

INTRODUCTION

Road accidents account for approximately 30% of traffic accidents worldwide and the dramatic increase of traffic accidents has become a critical problem of major concern to society in decades. In regular cases, fatigue or drowsiness, an intermediate state between wakefulness and sleep is a major factor that affects drivers and results in reduced arousal and slow reaction time, thus causing abnormal driving aptitude.

Ubiquitous healthcare (UH) with a wireless sensor network (WSN) framework offers great opportunities for measuring driver physiological signals in a centralized distributed sensor network with formidable capability to receive and organize multiple signals under a single network in a real-time environment. Given the present information and communication technology (ICT) trend that has expanded from UH, several studies have been conducted to investigate the relationship between vigilance and physiological signals that include HRV, electroencephalograms (EEG), blood pressure (BP), galvanic skin response (GSR), PPG, ECG and facial activity.

A Drowsy Driver Detection System uses a specially designed matlab based algorithm that points directly towards the driver's eyes in order to detect fatigue. In such a case when fatigue is detected, a warning signal is issued to alert the driver. The algorithm developed is unique to any currently published papers, which was a primary objective of the project. The system deals with using information obtained for the binary version of the image to find the edges of the face, which narrows the area of where the eyes may exist. Once the face area is found, the eyes are found by computing the horizontal averages in the area.

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Taking into account the knowledge that eye regions in the face present great intensity changes, the eyes are located by finding the significant intensity changes in the face. Once the eyes are located, measuring the distances between the intensity changes in the eye area determine whether the eyes are open or closed. A large distance corresponds to eye closure. If the eyes are found closed the system draws the conclusion that the driver is falling asleep and issues a warning signal. The system works under reasonable lighting conditions.

To overcome the limitations of current drowsiness detection methods, this proposed research aims to develop a real-time, easy implementable, nonintrusive and accurate drowsiness detection system. The development of technologies for detecting or preventing drowsiness at the wheel is a major challenge in the field of accident avoidance systems. Because of the hazard that drowsiness presents on the road, methods need to be developed for counteracting its affects. The aim of this is to develop a prototype drowsiness detection system. The focus will be placed on designing a system that will accurately monitor the open or closed state of the driver's eyes in real-time. By monitoring the eyes, it is believed that the symptoms of driver fatigue can be detected early enough to avoid a car accident [1-7].

Related Works: Estrada *et al.* [8] computed the relative EEG spectral powers that correspond to the intersection point between the alpha and beta frequencies in a single algorithm to detect sleep onset, but the results were unsatisfactory. Szypulska *et al.* [9] measured sleep syndromes based on HRV analysis in the LF/HF ratio; however, determining the possibility of a person being in the phase 1 of sleep required a minimum of 30 s. Similarly, Li *et al.* [10] predicted driver vigilance by analyzing the HRV frequencies derived from PPG and decomposed into VLF, LF and HF bands. Khedar *et al.* [11] analyzed drowsiness by proposing an extraction of the HRV features using the wavelet packet coefficient with adaptive threshold method.

On the other hand, Du *et al.* [12] combined feature selection with the time sequence energy analysis technique from eye opening and size of the pupil region to estimate driving drowsiness. Hemi *et al.* [13] ensured driver safety by relying on two distinct methods: (1) eye movement monitoring with an infrared sensor and (2) bio-signal processing with respiratory and HR sensors. However, the aforementioned studies did not demonstrate the effectiveness of sensors for accurately measuring the driver drowsiness state.There are several approaches for classifying driver drowsiness levels based on extracted features. Hu *et al.* [14] proposed methods for detecting drowsiness based on the EEGpower spectrum analysis. Raw EEG is filtered by applying an independent component analysis with reference (ICA-R) for electrooculography artifact removal; subsequently, the EEG spectrum features were extracted. Whereas Khushaba *et al.* [15] developed efficient fuzzy mutual information (MI)-based wavelet packet transform (FMIWPT) features-extraction method that maximized the amount of drowsiness-related information extracted from a set of EEG, EOG and ECG in order to classify the driver drowsiness state into predefined drowsiness levels.

Murata *et al.* [16] analyzed drowsiness by studying the relationship between EEG, HRV, tracking error and subjective fatigue rating. Then, Bayesian-based drowsiness prediction was proposed to calculate the probability of driver drowsiness level.Some reports in the literature employ physiological signals, such as the heart rate [7, 8], electroencephalogram (EEG) [9– 12], electrocardiograph (ECG) [13] and the respiration rate [14], to determine the driver's state. In [7], a new calculation method for respiratory sinus arrhythmia and Mayer waverelated sinus arrhythmia is derived from an analysis of heart rate variability, to evaluate the driver's mental stress and drowsiness.

Jap *et al.* [9] assessed four EEG activities, namely, delta, theta, alpha and beta, during a monotonous driving session. The results have implications for the detection of fatigue, based on an increase in the ratio of slow- to fast-wave EEG activities over time. Chua *et al.* [13] combined ECG and photoplethysmogram measurements to estimate psychomotor vigilance by establishing multiple linear regression models. Yang *et al.* [15] proposed a driver fatigue recognition model based on a dynamic Bayesian network that uses physiological features (ECG and EEG) and they applied the hidden Markov model (HMM) to compute the dynamics of the network at different points in time. To acquire the given signals, however, one or more intrusive sensors must be attached to the driver's body. This requirement makes most drivers unwilling to use the system and is impractical in most situations.

Proposed Methodology: Fig. 1 illustrates the conceptual design of the proposed smart device based drowsy driver prediction application. It consists of Multi modal(EEG,ECG,PPGand video frames) bio signal for drowsy level detection which are sensed by the sensor module (sensing). Then the proposed BJSFSD algorithm used to analyse the bio signal processing module.

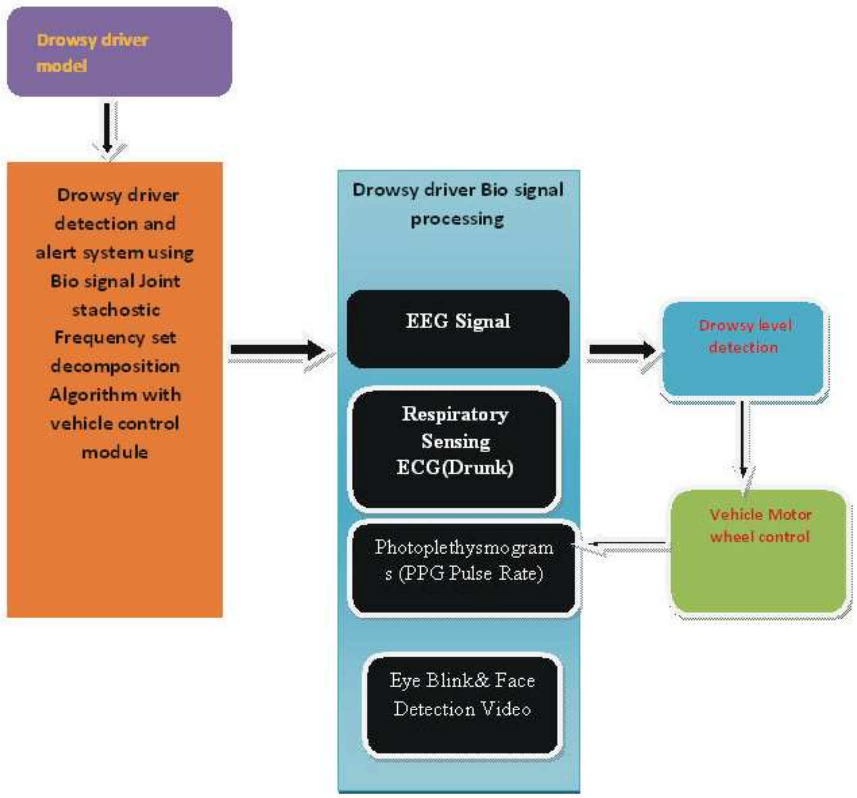


Fig. 2: General Architecture Of Proposed BJSFSD Design.

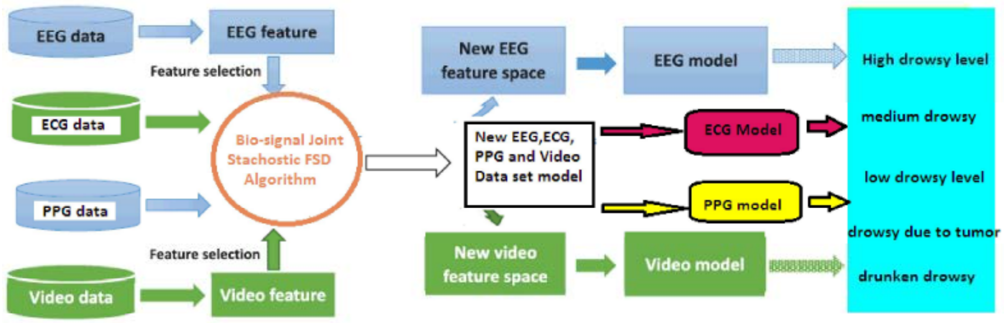
The sensing module senses ECG signals via conductance fabric and senses PPG signals via the driver's finger. all the EEG,ECG and PPG sensors are attached to the steering wheel; thus, body attachment is not required. As we mentioned earlier video camera is fixed to capture the driver eye blink and face detection. The received analog signals are further amplified and filtered before converting them into digital signals by our proposed controller modeule. Next, the signals are resamples theEEG, ECG and PPG signals into specified rate of sampling rate to detect the drowsy level. Based on the drivers drowsy level smart vehicle motor controlling device is used to control the vehicle motors

Once the controller receives these signals, the device first performs a low-pass filtering to remove AC noise. Then, RRs are derived from clean EEG,ECG signals. Derived respiratory waves are further averaged to obtain the final respiratory signals. A trained FCM classifier determines the probability of the driver vigilance level based on the features extracted from ECG, PPG and RR. Output information from the classifier is then displayed on the screen. If the drowsy level falls below a pre-defined threshold, vibration and ringtone warnings are triggered to alert the driver of their critical condition.

Bio Signal Joint Stachostic FSD Processing (BJSFSD): Fig. 2 shows the effective architecture of our proposed approach. seperate color represents the data flow of corresponding bio signal model. There are two phases in the design which are module 1 and module 2.

In module 1 based on the signal classification learning phase, there are four steps:

- EEG,ECG,PPG and video signals are sensed by data acquition and its features are extracted.
- Features are selected by statistical tests to check whether there exists significant difference in every feature between different groups of drowsy levels and emotions or tags.
- the correlation or Relationship between ECG,EEG, PPG signals and video content are exploited using FSD to co-construct a new EEG,ECG,PPG feature space and a new video feature space.
- For drowsy level detection using emotion recognition from EEG,ECG,PPG signals, a SVM classifier is trained on the new EEG,ECG,PPG feature space; For video emotion tagging, a SVM classifier is learned on the new video feature space.



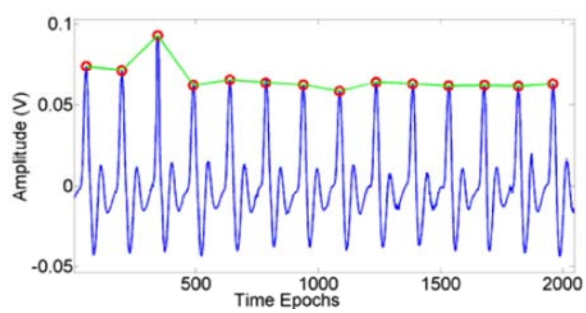
In the next module 2 explains about the testing phase, for emotion recognition from ECG, EEG and PPG signals, the extracted EEG features are transferred to the EEG feature space and the SVM classifier trained on the EEG space is used to recognize emotions; For video tagging, video features are transferred to new video features and the SVM classifier learned on the video space is adopted to assign emotion tags to videos.

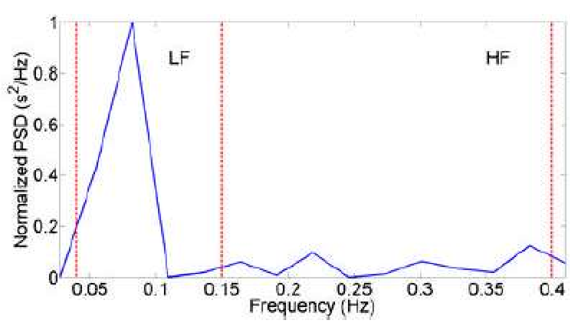
Signal Processing and Methods

EEG Processing: The general scheme of the EEG analysis is illustrated in Fig. 2. The acquired EEG data were processed and analyzed using an opensource EEG toolbox for MATLAB during the preprocessing stage; the raw EEG signals were subjected to a 1-Hz high-pass and 50-Hz low-pass infinite impulse response filter and then downsampled to 250 Hz from the sample recording rate of 500 Hz used during the hardware phase. The artifacts, such as one or more eye blinks or electromyography activity, were then removed from the filtered EEG data. After artifact removal, the data were sliced into segmented epochs based on the corresponding event tags associated with the recorded data.

EEG Features: First, noise mitigation is carried out. Horizontal lectrooculography (HEOG) and vertical electrooculography (VEOG) are removed and a Butterworth bandpass filter with a lower cutoff frequency of 0.3 Hz and a higher cutoff frequency of 45 Hz is used to remove dc drifts and suppress the 50 Hz power line interference. Then the power spectrum (PS) is calculated and is divided into five segments, which are the delta (0-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13–30 Hz) and gamma (30–45 Hz) frequency bands. The ratio of the power in each frequency band to the overall power is extracted as the feature.

Pulse Rate Variability Derivation (PPG): The pulse rate (PR) interval is calculated as the time interval of two successive peaks of the received PPG (see Fig. 3 first-order-derivative (FOD) at 8 s time epochs. The peaks are detected using the adaptive threshold method. Here, a virtual threshold initially set at zero value and is decreased with constant value along the signal amplitudes until it reaches an inflection point (IP). At this point, the peak position of a cycle of PPG signal is detected. After IP is reached, the threshold is decreased again by a modified slope parameter. The reason of adopting the modified slope parameter value is to avoid the false detection of other local maxima after the first true peak position in a complete one cycle of PPG signal.





The initial slope parameter for IP is defined in (1), whereas the modified slope parameter is updated as depicted in (2).

$$slope_{init} = 0.9\max(PPG_{FOD})$$

$$slope_k = slope_k + Sr \times \frac{(V_{n-1} + Std(PPG_{FOD}))}{Fs}$$

Where Slope k is the k-th slope amplitude, sr is the slope changing rate (0.6), Vn-1 is the previous peak amplitude, Std(ppg)is the standard deviation of FOD and Fs is the sampling frequency rate.

For the analysis purpose, PSD is subsequently grouped into very low frequency (VLF, 0.003 Hz – 0.04 Hz), low frequency (LF, 0.04 Hz – 0.15 Hz) and high frequency (HF, 0.15 Hz – 0.4 Hz) bands, where each demonstrated different variation pattern depend on the driver drowsy level. The frequency bands are grouped by the summation of wavelet coefficients. Grouping of the relative wavelet coefficients reflect changes in the signal with time in the frequency range of

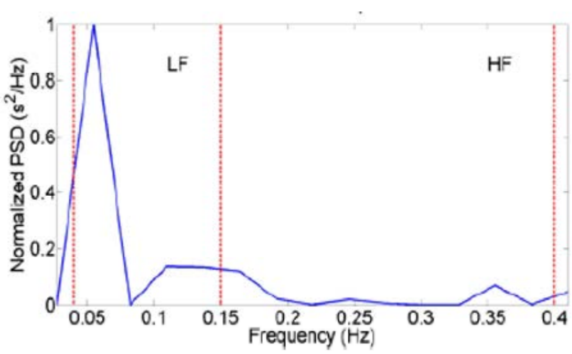
$$\left[\frac{(m-1)F_S}{2^{j+1}}, \frac{mF_S}{2^{j+1}}\right]$$

where Fs is the sampling frequency,m= 0,1,2 …, 2,jis the level of FSD decomposition.

Table I: describes the FSD wavelet packet decomposition at the 7-th level

FSD Wavelet Coefficients	Frequency Range	Frequency Band
W7,1-W7,2	0.00Hz-0.04Hz	VLF
W7,3-W7,6	0.04Hz-0.15Hz	LF
W7,7-W7,15	0.15Hz-0.40Hz	HF

Heart Rate Variability Derivation ECG: ECG is the manifestation of contractile activity of the heart, which is a valuable indicator of the individual's overall activity level. By other means, it is the recording on the body surface of the electrical activity generated by the heart. In fact, the cardiac rhythms and respiratory system do not work independently. They are highly correlated with the nervous system. Likewise, PPG, a non-invasive optical technique that measures the changes in skin blood volume and perfusion, also includes components synchronous with respiratory and cardiac rhythms.



The R-R interval is computed as the time interval of two successive R peaks of the ECG signal as illustrated in Fig. 4 which are denoted as the red 'O's. The R peaks are detected using the Pam-Tompkins method. The heart rates are estimated by multiplying the ECG sampling rate (256 Hz) with 60 s and divided by the interval between two consecutive R peaks. Next, the HR is decomposed into frequency domain using FSD-WPT method and normalized, which is denoted as HRV as depicted in Fig. 4. Likewise, the HRV power spectrum is grouped accordingly into VLF, LF and HF frequency bands based on the summation of wavelet coefficients. The decomposed frequency bands are defined as the same for PRV [15,16].

$$PSD_{PIH}(f) = PSD_{HRV}(f) \times \overline{PSD_{EDR}(f)}$$

$$PSD_{SIH}(f) = PSD_{HRV}(f) - PSD_{PIH}(f)$$

where PSD hrv is the power spectral density at the specified frequency range from 0.003 Hz to 0.4 Hz, whereas normalized PSD at interval [0, 1]. The ratio of above can be evaluated as a drowsy index, as shown in below

$$\mathrm{DI} = \frac{\sum_f PSD_{PIH}(f)}{\sum_f PSD_{SIH}(f)}$$

Visual-Audio Features: We extract both visual and audio features from videos. For visual features, lighting, color and motion are powerful tools to establish the mood of a scene and affect the emotions of the viewer according to cinematograph and psychology. Thus, three features, named lighting key, color energy and visual excitement are extracted from video clips. The details of features can be found in video features are extracted from videos, including average energy, average energy intensity, spectrum flux, zero crossing rate (ZCR), standard deviation of ZCR, 12 Mel-frequency cepstral coefficients (MFCCs), log energy of MFCC and the standard deviations [17].

BJSFSD Pseudocode
start
initialize days slot ts=time delay epoch.
Initialize the sensing levels of ECG,EEG,PPG and video details
Read input ie. measure the values of EE,EC,PP,and video
Φ=${EE,EC,PP,V}.
μ=?(Φ(EE,EC,PP,V)).
Ω - FSD decomposed mapping operation to find the values in Φ towards EE,EC,PP,V.

Ω- will return three different drowsy values- Normal, Moderate, Ubnormal.

Handover Ω to vehicle controller.

For each second of t epoch.

for [illegible] do

Train classifiers using [illegible] and calculate the Correlation for FSD.

Generate learningFSD Set.

FSD = FS+ Σ($\int_1^N (V \times M.K + E)$). // rule.

M- number of functions per second.

E-Eye blink datas

For each Function from Fs

Generate FSD set for EE,EC,PP measurement.

BJSFSD= $\sum_{i=1}^{size(Fi)} \sum Crop(Fi, B, C)$

End

For each Measure ruleset value Dl from BJSFSD

Compute drowsy level of Dl.

Motor= drowsy measurement (Dl).

K=values of the EC,EE,PP peak counts

Identify feature mass point Fmp.

Fmp = $\sum_{i=1}^{sizeDl} \sum Pi(Si).Neighbors\ sets \simeq Max(Dl)$

Compute Number of neighbors with more feature value.

MFVP = $\sum_{i=1}^{size(si)} \sum Pi(Dl) \geq Max(Dl)$

Compute regulation of Drowsy level.

Std Dl = Stddev(Dl).

Generate Feature Descriptor FSD.

BJSFSD= {EE,EC,PP, MFVP, StdInsulin}.

Add to feature descriptor set BJSFSD.

BJSFSD = $\sum FSD(BJSFSD) \cup FSDI \cup DI$

[illegible]

(training values)

End

End

Experimental Results and Analyses: To evaluate the proposed research, we conducted four experiments. First, we evaluated the effectiveness of the proposed feature selection methods, whereby we identify the EEG channels and video features that are most effective for emotion recognition and video emotion tagging. Second, we evaluated the performance of the proposed method for emotion recognition from EEG signals against the baseline method. Third, we evaluated the performance of the proposed method for video emotion tagging against the baseline method. Finally, we compared our methods with state of the art methods that perform explicit multimodal fusion.

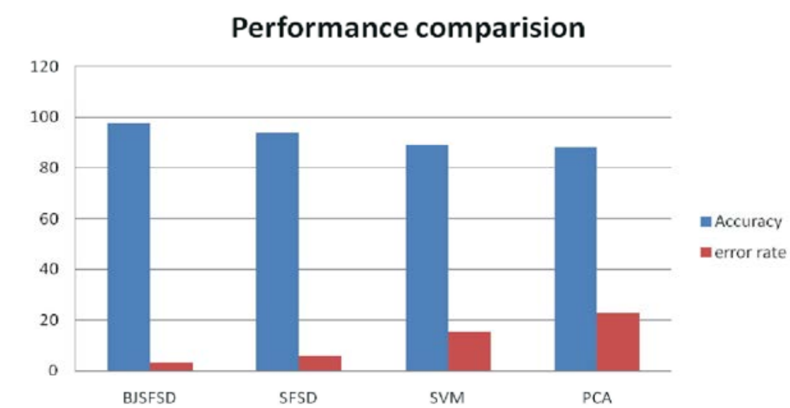


Fig. 8: Performance comparasion

Table 1: Comparative results of different algorithm

Method/Algorithm	Feature	Error rate	Detection rate	Accuracy level (%)
PCA	EEG	22.71	75.61	88
SVM	Facial features	15.24	81.24	89
Stachostic FSD	EEG+Eye blink+face tilting	5.94	92.34	94
BJSFSD	EEG,ECG,PPG,Video	3.24	96.56	98

For better evaluation of ability of each feature in distinguishing of alert and drowsy classes, we have used a classifier. Accuracy, error rate and specificity detection rate of classification are shown in Table.

From the comparison results shows that the Proposed FSD has better evaluation of ability of each feature in distinguishing of alert and drowsy classes with the accuracy of 94%. Accuracy, error rate and specificity detection rate of classification are shown in Table 1.

CONCLUSION

The amplitude of an EEG signal fluctuates on the microvolt level, making the EEG signal extremely noise-sensitive and easily influenced by artifacts. In addition, the EEG features between different subjects usually vary widely, making it difficult to apply and generalize results from one individual to another. The proposed EEG signal-processing procedures and method in this study overcome these two limitations. This is justified as the FSD algorithm selects the required components for each subject by estimating the EEG signal analysis between these components. The proposed work shows the achievement for the drowsy level accuracy of 98 % EEG based drowsiness detection system. The Stay Alert system can be further modified to include a variety of devices that take into consideration behavioral, physiological and vehicle-based parameter to determine the sleepiness level of a driver. Devices to detect lane drift, drooping of eyes, slowing of heart rate, etc. can also be included in the system. This would greatly increase the accuracy of the system and prevent false alarms.

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