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SCIENTIFIC PAPER

Detection and analysis: driver state with electrocardiogram (ECG)

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Abstract

Driver drowsiness, fatigue and inattentiveness are the major causes of road accidents, which lead to sudden death, injury, high fatalities and economic losses. Physiological signals provides information about the internal functioning of human body and thereby provides accurate, reliable and robust information on the driver's state. In this work, we detect and analyse driver's state by monitoring their physiological (ECG) information. ECG is a non-invasive signal that can read the heart rate and heart rate variability (HRV). Filters are applied on the ECG data and 13 statistically significant features are extracted. The selected features are trained using three classifiers namely: Support Vector Machine (SVM), K-nearest neighbour (KNN) and Ensemble. The overall accuracy for two-classes such as: normal–drowsy, normal–visual inattention, normal–fatigue and normal–cognitive inattention is 100%, 93.1%, 96.6% and 96.6% respectively. The result shows that two-class detection provides better accuracy among different states. However, the classification accuracy using Ensemble classifier came down to 58.3% for five-class detection. In the future, better algorithms have to be developed for improving the accuracy of multiple class detection.

Keywords Electrocardiogram · Drowsiness · Visual inattention · Cognitive inattention · Fatigue

Introduction

Road accidents are occurring frequently due to human mistakes. From the statistical report for the year 2017, though the number of accidents have reduced, the fatalities are still growing high [1]. To overcome these fatalities, death rate and economic loss, many technologies have been developed in automobile industries such as the 'Advanced Driver Assistance System (ADAS)' which continually monitors the behavioural states of the driver and alerts them when required. Various internal conditions of a driver such as drowsiness, fatigue, visual and cognitive inattentive, stress, alcohol consumption etc., are monitored by ADAS systems deployed in various vehicles [2]. These systems work with the input from multiple data sources like images, videos, LiDAR, radar, ultrasonic and in-car telematics. Physiological signals acquired from the driver are also an input source which can predict the driver drowsiness, fatigue and inattention before leading to an accident. Researchers have used various physiological signals like Electromyography (EMG), Electro-oculography (EOG) and Electroencephalography (EEG) to detect hypovigilance. EEG signals are acquired using a 10–20 electrode cap system which is quite inconvenient and intrusive for the driver. These signals are also prone to artefacts due to eye blinks, heart activity and other movements which in turn increases the computational complexity and performance of the algorithm. EOG signals are picked up from the electrodes that are placed near the eyes disturbing the driver while driving [3]. Installing an EOG based system on real time may also be difficult [4]. This work focused on ECG signals to detect hypovigilance as it has two lead system that can be easily adopted to wearable devices and a number of research works indicate correlation between internal states and ECG [5, 6]. Drowsiness is a condition of a driver who is fatigued enough for driving a car or a sleepy condition of a driver which causes the driver unable to drive properly [7]. Drowsiness will not appear instantly, but, will emerge with some symptoms which generally occur in every driver [4]. Drowsiness is categorised as three stages: slightly drowsy, moderately drowsy and extremely drowsy. Inattention occurs in two

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ways: visually inattention and cognitive inattention. Visual inattention is driver getting distracted while driving by reading message on phone, viewing something out of track from their focus of driving. Cognitive inattention is distraction to driver by attending phone calls, thinking deep on something, etc. From the definition of European Transport Safety Council (ETSC), the fatigue is a state that concerns the inability or disinclination to continue an activity generally because the activity has been going on for too long [8]. Driver fatigue is synonymously used with driver drowsiness. Driver inattention or distraction is a diversion away from activities critical for safe driving toward a competing activity [9]. Hypovigilance means 'diminished alertness' or anything that causes a decrease in paying a close and continuous attention. Impairment of alertness in a driver may be due to prolonged sleepiness or short term inattention [10].

ECG is a non-invasive signal which does not harm drivers while driving. ECG signals are easy to capture and less intrusive compared to other physiological signals and a number of features are derived by researchers to identify the various internal states and pathological conditions of the heart [11]. The Heart Rate Variability (HRV) signals that can be derived from ECG signals are highly resistant to noise and are found to be an effective marker in identifying the internal states. The linear and nonlinear analysis using time and frequency provides enormous information about HRV [12] and many researchers have worked on detection of drowsiness [13, 14], fatigue [15–18] and inattention [19] using HRV. A combination of heart rate and breathing rate is also found to be good indicators of drowsiness [20]. A non-intrusive method of acquiring ECG using as a Bluetooth device with ECG or Heart Rate sensors that is attached at steering wheel, or chest electrodes attached to the clothes are developed by researchers for recording ECG signals unconsciously from the driver [13]. However, such non-intrusive systems, provide lesser accuracy and are prone to movement artifacts and errors that occur because of improper electrode contact [21].

The raw ECG data collected from drivers through various means consist of noises and artifacts due to varied causes. Filtering techniques using Finite Impulse Response (FIR) or Infinite Impulse Response (IIR) filters with cut off frequencies ranging from 3 to 100 Hz are used to remove the effect of noises and artifacts from ECG signals [22]. The FastICA is used to estimate the independent components from observed mixture X, which is obtained from mixing model as $X = AS$, where A is an unknown mixing matrix, and S is unknown source signal [23]. FastICA seeks an orthogonal rotation of data, through a fixed-point iteration scheme that maximizes the measure of non-Gaussianity of the rotated components which can separate EMG and ECG from the original signal [18]. The heartbeats are detected by QRS complex delineator using Pan and Tompkins algorithm [24]. HRV signal is obtained by measuring the R peak from the ECG accurately based on the wavelet transform technique [17].

Features pertaining to the physical and internal states are derived from the pre-processed ECG signals. Features like Root Mean Square Standard Deviation (RMSSD), standard deviation of normal RR-interval (SDNN), HRV, triangular index, spatial filling index, central tendency method, correlation dimension, approximate entropy, proportion of NN20 (pNN20) [12]; Heart rate RR-interval QRS complex, R peak [25]; Pulse Arrival Time (PAT), respiratory rate [13]; sample entropy, complexity of ECG [18] are extracted by researchers to identify the internal states. Additionally, various time frequency-based analysis such as Fast Fourier Transform (FFT), Hilbert-Huang Transformation (HHT), Empirical Mode Decomposition (EMD) and Discrete Wavelet Transform (DWT) are used to derive features. HHT is known as a nonlinear and nonstationary data analysing method and it works with two main functions namely EMD and intrinsic mode function (IMF) [26].

The acquired features are then classified using classifier algorithm for evaluating the detection performance. Case-Based Reasoning (CBR) system that classifies 'healthy' and 'stressed' persons based on the fusion of multiple sensor data [13]. In order to obtain the uncorrelated variables and avoid pseudo regression, the Principal Component Analysis (PCA) is used in analysing the physiological features with an accuracy of 91% and is compared to the Multiple Linear Regression, a statistical method to study the linear relation between one dependent variable and multiple independent variables which provides an accuracy of 7.99% and 92.01% respectively [18]. Naïve Bayes is a classifier based upon the principle of Maximum A Posteriori (MAP) and its main drawback is low precision [27]. In the regression tree method, a tree is created in which each internal node is an input feature but suffers from a relatively low sensitivity [27].

In this research, the hypovigilance states such as normal, drowsy, fatigue, visual and cognitive inattention are identified using video recording. The ECG data are labelled accordingly. The raw data is exposed to noises and movement artifacts and therefore is preprocessed. The time domain linear and frequency domain non-linear features are extracted from ECG signal and the features are reduced by selecting only statistically significant features using one-way ANOVA test. The ANOVA features are again tested with PCA for feature selection and classified using three classifiers: SVM, KNN and Ensemble classifier. The comparison between fusions of two-class detection proves better accuracy than five-class detection. Similarly, among all the three classifiers, the Ensemble provides better performance for multiclass detection.

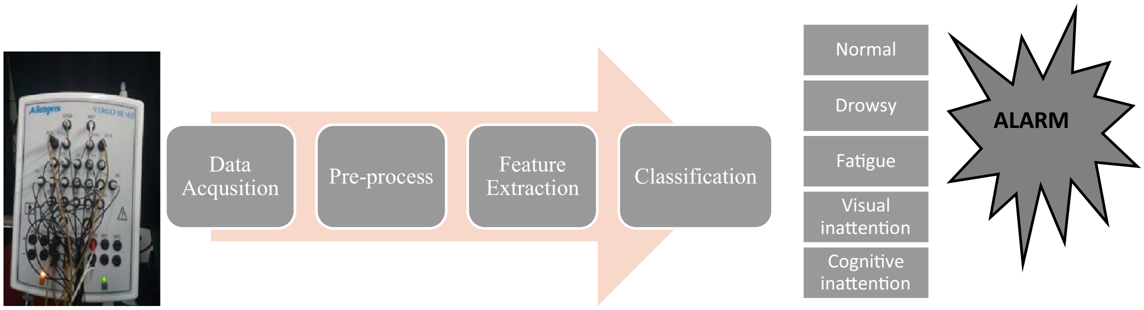

Fig. 1 Methodology to detect driver hypovigilance

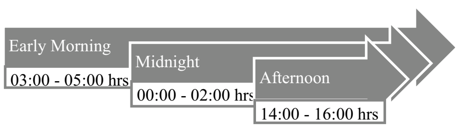

Fig. 2 Data collection experiment timings

Materials and methods

The methodology used for developing a hypovigilance detection system is shown in Fig. 1. Initially the physiological data is acquired, pre-processed to remove noises, features are extracted and classified to detect the hypovigilance states (normal, drowsy, fatigue, visual inattention and cognitive inattention). Based on the continual hypovigilant state of the driver, the data is classified.

Data acquisition

One of the most crucial step in developing an algorithm for the detection of driver states using physiological data is the acquisition of physiological data pertaining to the driver's internal states. As physiological data cannot be manipulated, the various states should be induced internally. In order to achieve proper simulation of data, the data collection experiment was planned during the different times of the day when the circadian rhythm is low as indicated in Fig. 2 [28].

Protocol for data acquisition

Figure 3 encapsulates the protocol designed for a continuous 2 h driving session to collect physiological data by simulating the various internal states of the driver such as normal, drowsy, visual inattention, cognitive inattention and fatigue. The 'Normal' state data was collected during the initial 15 min of driving after which 'Visual Inattention' was induced by sending SMS for three times for which the drivers had to respond while driving. Simple questions such as (i) unforgettable moment in their life, (ii) tell about your country, (iii) tell about reasons for road accidents, (iv) tell something on your like and dislike etc., were asked to the drivers to visually distract them from driving. Then the driver was allowed to drive for the next 15 min. Then, they were subjected to answer mathematical questions (addition and subtraction) with increasing complexity which made them to think and reply while driving. Thereby, Cognitive Inattention data was captured. After this, they were allowed to continuously drive for 80 min or until the time when the driver falls asleep. The session stops once the driver is unable to control his sleep.

Experimental setup

The experiment was conducted at Artificial Intelligence Research Laboratory, Vels University, Chennai. The Experimental setup is shown in Fig. 4. The driving simulator used for driving is installed with Speed Dreams 2.2.1, a game which enables a monotonous driving environment and the speed limit was set at 80 km/hr. The game track was chosen as 1-mile, low banked oval speedway. Allengers Virgo SL-40 Polysomnography (PSG) device with 21—EEG channels, 2—ECG, 2—EOG, 2—EMG, 2 SpO2 and heart rate, body position sensor, 2 effort channels (abdominal and thoracic), 2 limb movement,

Fig. 3 Protocol design for experiment

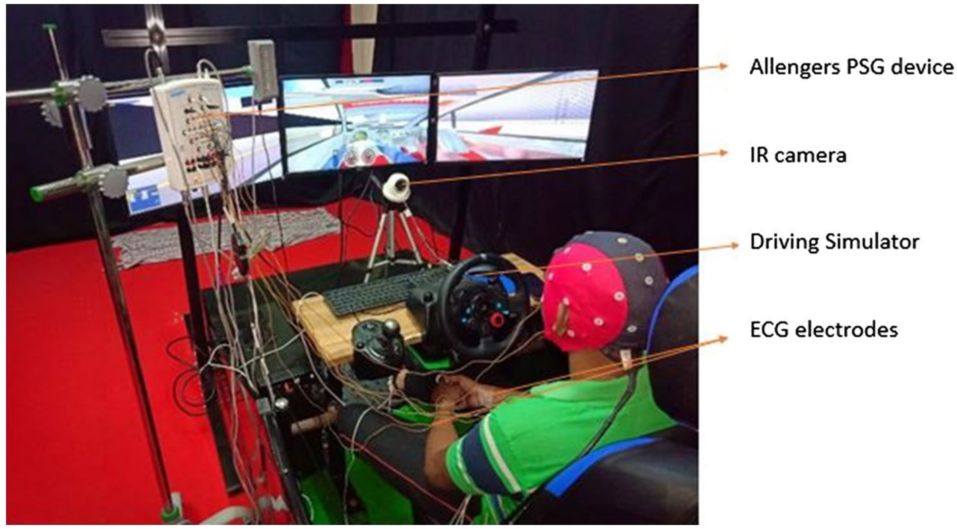

Fig. 4 Experimental setup

Fig. 5 ECG electrode placed

nasal/oral airflow/pressure, snoring, 4 auxiliary channels, 2 bipolar channels and event marker was used for data collection at a sampling rate of 256 Hz. The ECG electrodes are placed on left and right wrist of the drivers hand for recording as shown in Fig. 5. HIK VISION IRPF camera which can switch the video output mode like TVI/CVBS/AHD/CVI is used to record video for the entire 2 h of driving session.

Data acquisition

Ten licensed drivers (9 male and one female) between the age group of 19–35 years with valid driving license participated in data collection experiment. The drivers were explained on the protocol and asked to fill their individual details and consent form. Each driver was provided with an honorarium for their session. The drivers were provided with forms to fill—a set of pre-questionnaires before driving and set of post-questionnaires after driving. Electrodes were placed on the driver as shown in Fig. 4. ECG data was captured using the electrodes placed on driver's wrist. The drivers were then allowed to get familiar with the track by practicing on the environment for 10–15 min. The various states were stimulated in accordance with the protocol as in Fig. 3. The video and physiological signals are time coordinated to enable proper splitting of physiological data for further processing.

Pre-processing of ECG data

The raw signal contained baseline wandering, peaks and noises caused due to movement and other artefacts during the data acquisition process [18]. The morphology of the ECG signal was disturbed with R peaks of diverse heights resulting in ambiguity. R peaks which were beyond the threshold value of 3000 µV created an illusion of R peak. The ECG signal reconstruction algorithm that provides a QRS component to find the possible R values by initializing the distance between QR and RS, slope of QR and slope of RS from the raw signals was used to remove false R peaks. The slope and distance between previous and next data is calculated to detect R peaks. The Q and S points that are situated before and after R is captured based on slope of QR and slope of RS at 200 µV to identify the QRS of the entire ECG data. The reconstruction algorithm (Fig. 6) enabled to remove false peaks, baseline wandering and other artefacts due to motion. The Fast Fourier Transform (FFT) reduces the complexity of the R value and is therefore used. The signals were then filtered using Butterworth 6th order filter for low cutoff frequency at 0.5 Hz and high cutoff frequency at 49 Hz as the useful information for detecting internal states in ECG lies in this frequency range [23, 24]. The filtered signal provides information for deriving HRV. The index of R is converted to absolute value and subtracted from the very next R index. This difference in R-R interval provides the HRV information for feature based extraction.

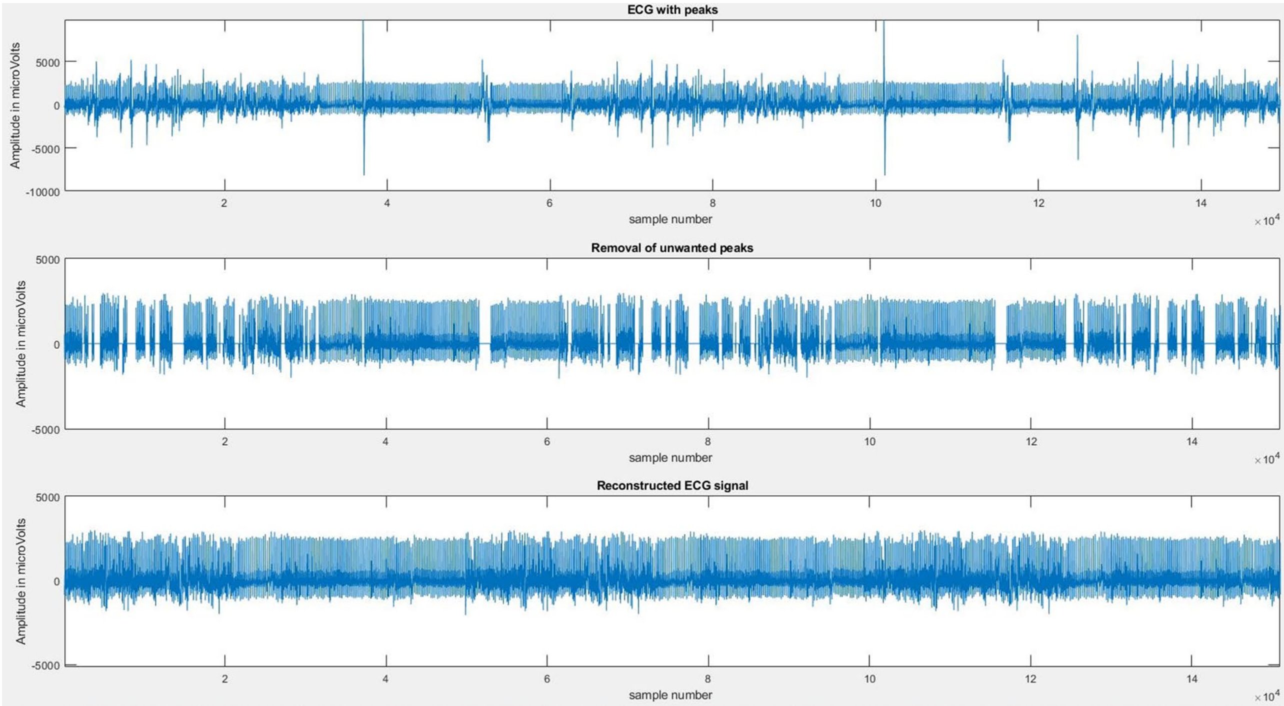

Fig. 6 Reconstructing the peaks in raw signal

Feature extraction

The filtered ECG signal is processed for extracting features that can detect the various hypovigilance states. A total of twenty features including Fourteen Time domain linear features namely mean, median, standard deviation (SD), First Quartile (Q1), Second quartile (Q2), Third quartile (Q3), Interquartile Range (IQR), maximum, minimum, variance, skewness, kurtosis, root mean square (RMS), power and energy, and three Frequency domain non-linear features such as Approximate Entropy (ApEn), Central Tendency Measure (Nanmean, Trimmean, Harmonic Mean) and Hurst exponent were extracted from the filtered ECG signals as tabulated in Table 1.

Table 1 Features extracted from filtered signals

Features	Equations	Features	Equations
Mean	$\mu_x = \frac{1}{N}\sum_{n=1}^{N} x_n$	Variance	$Var(X) = E\left[(X-\mu)^2\right]$
Median	$\frac{N+1}{2}$	Skewness	$\frac{\sum_{n=1}^{N}(x_n-\mu_x)^3}{(N-1)\sigma_x^3}$
Standard deviation	$\left(\sigma_x\right) = \frac{1}{N-1}\sum_{n=1}\left(x_n-\mu_x\right)^2$	Kurtosis	$\frac{\sum_{n=1}^{N}(x_n-\mu_x)^4}{(N-1)\sigma_x^4} - 3$
First quartile	$Q1 = \frac{n+1}{4}$	Energy	$\sum_{n=1}^{N} x_n^2$
Root mean square	$x_{rms} = \sqrt{\frac{1}{n}\left(x_1^2 + x_2^2 + \cdots + x_n^2\right)}$	Approximate entropy	ApEn (m,r,N) = $Ø^{m}$(r) – $Ø^{m+1}$(r)
Second quartile	$Q2 = \frac{n+1}{2}$	Maximum	$\max\left(x_n\right)$
Third quartile	$Q3 = \frac{3(n+1)}{4}$	Hurst	$E\left[\frac{R(n)}{S(n)}\right] = C_n^H asn \to \infty$
Interquartile range	$IQR = Q3 - Q1$	Minimum	$\min\left(x_n\right)$
Harmonic mean	$m = \frac{n}{\sum_{i=1}^{n}\frac{1}{x_i}}$	Power	$x(t) = \frac{1}{N}\sum_{i=1}^{N} p_i$

Classification of hypovigilance states

The extracted features were analysed using one-way ANOVA for statistical significance and features with p value less than 0.05 ($p < 0.05$) were chosen for further analysis. The features were also reduced using Principal Component Analysis (PCA) and classified using SVM, KNN and Ensemble classifiers. 75% of the acquired data were used for training the classifier and 25% for testing. SVM is a classical binary classification algorithm by minimizing the structural risk, finding the optimal linear decision surface between classes [29]. KNN is a supervised machine learning algorithm which classifies various hypovigilance states using Auto Regressive features and performs better than Quadratic Discriminant Analysis (QDA) and Linear Discriminant Analysis (LDA) [30]. Ensemble learning divides multiclass classification problem into binary classification problems by an encoding rule and decodes binary classification results to multiple classes by a decoding rule [19].

The performance of the developed algorithm and classifiers were calculated using,

$$\%Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Results

ECG filtering

The first plot in Fig. 6 shows the raw ECG signal with unwanted peaks; second plot shows the removal of unwanted peaks and by making the amplitude values of peaks to zero; and third plot shows the removal of zero values and reconstructing the ECG signals.

The reconstructed ECG signal has amplitudes of R wave and its corresponding index. Since R is an amplitude value, we need to convert it into frequency domain. Figure 7 shows the plot on the raw signal and Butterworth filtered ECG signals after FFT. The raw ECG is filtered by Butterworth 6th order filter between the cutoff ranges of 0.5 to 49 Hz.

Figure 8 shows the HRV information in the filtered ECG signal with difference in R-R interval.

Statistical analysis pertaining to driver states

All the 20 features were tested for statistical significance using ANOVA. Table 2 shows that 15 of the total 20 features are statistically significant for five class detection. The features like Mean, Power, IQR, Nanmean, Trimmean, Harmonic Mean, Approximate entropy and Q1 has $p < 0.05$ and were used for classification.

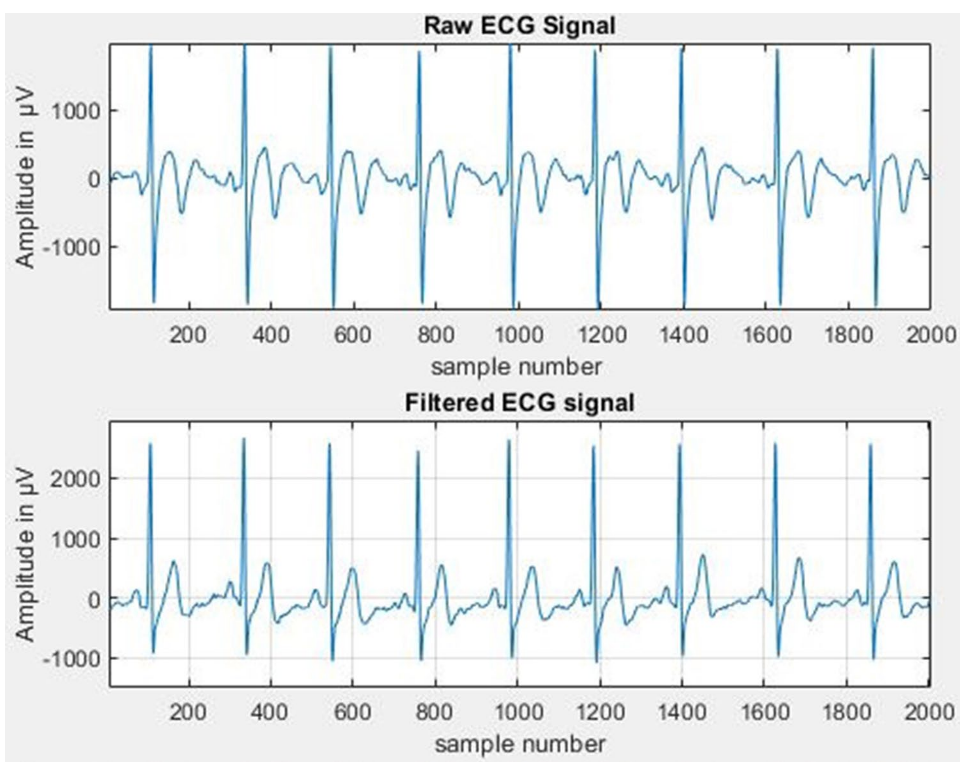

Fig. 7 Raw and filtered signal

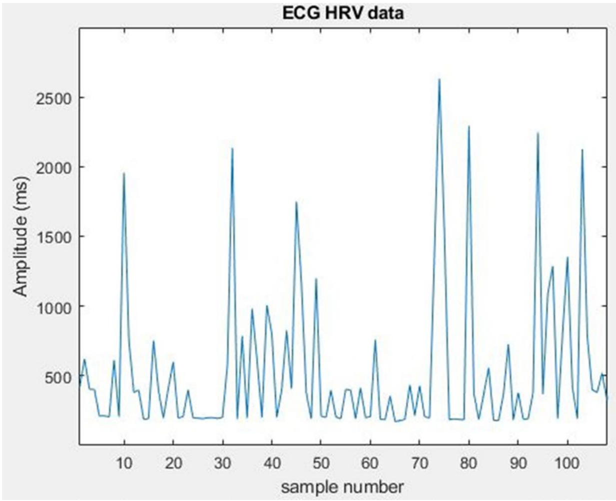

Fig. 8 HRV data in filtered ECG

Classification of driver states

The characteristics of the driver states namely drowsy, fatigue, visual inattention and cognitive inattention were initially understood by classifying each of these states with the normal state. Table 3 tabulates the performance of the statistically significant features in classifying the drowsy, fatigue, visual inattention and cognitive inattention respectively with the normal state. The statistical features namely mean, minimum, standard deviation, variance, RMS and energy gave better accuracy of 100% between Normal and Drowsy; the Hurst non-linear feature produced an accuracy of 82.8% between Normal and Fatigue; the Q1 feature performed better with an accuracy of 82.8% between Normal and Visual Inattention; the minimum feature performed better by producing an accuracy of 86.2% between Normal and Cognitive Inattention. From Table 3, we can infer that Ensemble performed better than other classifiers.

Table 4 shows the performance measured by fusion of hypovigilance states with respect to normal state for all three classifiers. From the Table 4, we can note that the accuracy obtained for two-class detection is high. The maximum accuracy obtained between normal and drowsy is 100% for 8 significant features like mean, minimum, standard deviation, variance, skewness, nanmean, RMS and energy; between normal and fatigue is 96.6% for 9 significant features like standard deviation, variance, Q1, hurst, RMS, energy, nanmean, trimmean and IQR; between normal and visual inattention is 93.1% for 13 significant features like mean, minimum, standard deviation, variance, hurst, Q1, IQR, RMS, power, energy, nanmean, harmonic mean and trimmean and between normal and cognitive inattention is 96.6% for 9 significant features like mean, minimum, standard deviation, variance, hurst, RMS, power, energy and nanmean. From the results, it can be observed that the nanmean feature is common among all the two-class detection which is the same as mean value but omitting NaN values.

Table 5 presents the performance on features which were statistically significant for five class detection using three classifiers. In SVM classifier, the higher-order statistical feature skewness performed best among all the other features with a maximum average accuracy of 41.7%. The minimum performed better than the remaining features with a maximum average accuracy of 36.1%. In KNN classifier, the statistical feature variance performed best among all the other features with a maximum average accuracy of 44.4%. The minimum performed better than the remaining features with a maximum average accuracy of 43.8%. In Ensemble classifier, the linear feature minimum performed best among all the other features with a maximum average accuracy of 50%. The variance feature performed better than the remaining features with a maximum average accuracy of 44.4%.

Table 2 Selection of statistically significant features

Features	Significant difference ($p < 0.05$)	Features	Significant difference ($p < 0.05$)
Mean	**0.002**	Q1	**0.005**
Median	0.277	Q2	0.277
Standard deviation	**0.000**	Q3	0.533
Variance	**0.000**	IQR	**0.007**
Maximum	0.154	Energy	**0.000**
Minimum	**0.000**	Root mean square	**0.000**
Hurst	**0.000**	Kurtosis	**0.000**
Approximate Entropy	0.059	Skewness	**0.000**
Power	**0.015**	Nanmean	**0.002**
Harmonic mean	**0.007**	Trimmean	**0.014**

The statistically significant features ($p < 0.05$) are bolded

Table 3 Performance on individual states with respect to normal state

Features	Classifier	Accuracy %			
		Normal–drowsy	Normal–fatigue	Normal–visual inattention	Normal–cognitive inattention
Mean	SVM	**100.0**	62.1	65.5	69.0
	KNN	**100.0**	65.5	65.5	69.0
	Ensemble	**100.0**	58.6	65.5	69.0
Minimum	SVM	**100.0**	55.2	65.5	69.0
	KNN	**100.0**	69.0	65.5	**86.2**
	Ensemble	**100.0**	72.4	65.5	**86.2**
Standard deviation	SVM	**100.0**	65.5	65.5	69.0
	KNN	**100.0**	72.4	65.5	65.5
	Ensemble	85.7	72.4	69.0	65.5
Variance	SVM	85.7	62.1	58.6	69.0
	KNN	**100.0**	69.0	65.5	69.0
	Ensemble	**100.0**	69.0	69.0	69.0
Hurst	SVM	71.4	75.9	79.3	69.0
	KNN	71.4	75.9	75.9	72.4
	Ensemble	85.7	**82.8**	75.9	69.0
skewness	SVM	85.7	51.7	58.6	65.5
	KNN	85.7	55.2	58.6	69.0
	Ensemble	85.7	55.2	65.5	75.9
Kurtosis	SVM	71.4	51.7	55.2	69.0
	KNN	71.4	48.3	62.1	65.5
	Ensemble	85.7	51.7	65.5	65.5
First quartile	SVM	57.1	65.5	65.5	51.7
	KNN	71.4	72.4	79.3	65.5
	Ensemble	71.4	69.0	**82.8**	72.4
Interquartile range	SVM	42.9	75.9	65.5	51.7
	KNN	71.4	69.0	65.5	58.6
	Ensemble	71.4	72.4	69.0	65.5
Root mean square	SVM	**100.0**	65.5	69.0	69.0
	KNN	**100.0**	75.9	72.4	65.5
	Ensemble	**100.0**	69.0	72.4	65.5
Power	SVM	57.1	55.2	72.4	58.6
	KNN	71.4	51.7	69.0	62.1
	Ensemble	71.4	58.6	55.2	58.6
Energy	SVM	85.7	72.4	72.4	75.9
	KNN	**100.0**	62.1	69.0	75.9
	Ensemble	**100.0**	69.0	62.1	69.0
Harmonic mean	SVM	71.4	58.6	58.6	72.4
	KNN	57.1	65.5	65.5	79.3
	Ensemble	71.4	55.2	62.1	65.5
Nanmean	SVM	**100.0**	62.1	65.5	69.0
	KNN	**100.0**	65.5	65.5	69.0
	Ensemble	**100.0**	58.6	65.5	69.0

The highest accuracy are in bold

The maximum accuracy obtained among 15 features is 50% for Minimum in Ensemble classifier. Table 6 provides the feature wise accuracy obtained for fusion of features in five classes (Normal, Drowsy, Fatigue, Visual and Cognitive Inattention) detection with three machine learning classifiers: SVM, KNN, and Ensemble. Table 6 indicates the performance of classifiers in identifying all the five hypovigilance states. It can be observed that, Ensemble classifier obtained

Table 4 Performance of hypovigilance features

Performance of hypovigilance features				
Classifier	Normal–drowsy (%)	Normal–fatigue (%)	Normal–visual inattention (%)	Normal–cognitive inattention (%)
SVM	100	96.6	86.2	93.1
KNN	100	96.6	82.8	96.6
Ensemble	100	89.7	93.1	86.2

an accuracy of 56.9% using the 15 features that were statistically significant. Four features namely Minimum, variance, skewness and harmonic mean were selected after applying PCA and the accuracy of the features are tabulated in Table 7. A maximum accuracy of 58.3% was obtained using Ensemble classifier. The Ensemble classifier shows the better results compared to the other two classifiers in categorizing five driver states.

Based on the overall accuracy obtained on fusion of different combinations of classes, the performance chart is as shown in Fig. 9; it displays the abbreviated combination of classes for comparison where N-Normal, D-Drowsy, F-Fatigue, V-Visual Inattention and C-Cognitive Inattention. The comparison chart is prepared based on the fusion of features at different classes and the chart (Fig. 9) indicates accuracy obtained for KNN, SVM and the Ensemble classifier. The chart displays the accuracy values obtained for fusion of two-class, three-class, four-class and five-class performances. The accuracy values gradually decrease when we increase the number of classes in fusion. From the chart, the accuracy obtained for two-class is high when compared to the five-class combination. But, the five-class category detects a greater number of classes when compared to the two-class detection. Also compared with three classifiers used, the Ensemble provides the better accuracy in fusion of features of classes combined and for the individual feature wise accuracy. This concludes that Ensemble is the better classifier when we go for the multiclass detection.

Discussion

ECG data acquisition

In this work, the ECG bipolar electrodes are placed on the driver's left and right hand wrist with conductive gel (Ag/AgCl) and medical tape which is less adhesive on human skin. It provides poor contact of the electrode during steering movements. Due to the misplacement of non-intrusive electrodes, there are more unwanted peaks occurring in the signal. This may lead to lesser accuracy, as the signals are prone to movement artifacts and errors. The ECG data which is acquired may also get contaminated with EMG signal artifacts, as the ECG collected from the muscles also carries EMG information. So there is need for proper filtering without any data loss. The development of non-intrusive wireless technologies like Bluetooth or Zigbee by placing ECG electrodes on the steering wheel or in the driver's seat can provide less accurate information due to the lack of improper electrode contact [31]. So it is a real challenge to develop a non-intrusive wireless wearable device which can manage to provide good flow of information without much data loss and effective filtering techniques have to be developed to remove artifacts.

Hypovigilance detection performance

The result demonstrates that the best overall accuracy for two-class detection is 100% for normal with drowsy because of the time domain features mean, minimum, standard deviation, variance, RMS and non-linear feature Nanmean. For normal with visual inattention the overall accuracy obtained is 93.1% for the first quartile (Q1) feature. For normal with cognitive inattention the overall accuracy obtained is 96.6% for the minimum feature. Similarly, for normal with fatigue the overall accuracy obtained is 96.6% by the non-linear feature Hurst exponent feature. Hurst exponent which is a Rescaled Range Statistical feature performs better as it does not require any parameter selection and the time reversal feature of Hurst only involves selection of time lag [32].

The linear features are combined with non-linear features for two-class detection which provides good accuracy. Researchers have observed that combining linear and non-linear features provides significant improvements in the class separability with embedding parameter selection methods [32]. For five-class, the linear feature namely: minimum provides accuracy of 50%. In this work, SVM, KNN and Ensemble classifiers are used and among them Ensemble provides the better performance for five-class. The ensemble classifier provides better accuracy compared to the other classifier as it uses bagging strategy [33]. PCA applied to the features provides the overall accuracy for five-class as 58.3%. The increase in PCA reduced features provides better accuracy and this is in line with the observations made by other researchers [18, 34]. From the result, it can be observed that in detecting five-class driver state, the classification accuracy gets reduced compared to the two-class detection. To improve the classification accuracy of algorithms across subjects, deep learning algorithm can be considered for future.

Table 5 Performance on ANOVA features

Performance on ANOVA features for five class detection							
Features	Classifier	Normal (%)	Drowsy (%)	Fatigue (%)	Visual (%)	Cognitive (%)	Average (%)
Mean	SVM	7.1	73.3	21.4	7.1	20	26.4
	KNN (6)	50	40	21.4	14.3	26.7	30.6
	Ensemble	50	46.7	21.4	14.3	20	30.6
Minimum	SVM	64.3	21.4	35.7	6.7	53.3	36.1
	KNN (5)	37.5	56.3	37.5	43.8	43.8	43.8
	Ensemble	57.1	71.4	28.6	26.7	66.7	**50**
Standard Deviation	SVM	42.9	7.1	7.1	53.3	53.3	30.6
	KNN (7)	25	56.3	37.5	25	37.5	36.3
	Ensemble	64.3	7.1	28.6	13.3	46.7	30.6
Variance	SVM	14.3	66.7	64.3	21.4	6.7	34.7
	KNN (7)	50	73.3	35.7	14.3	46.7	44.4
	Ensemble	35.7	73.3	28.6	14.3	66.7	44.4
Hurst	SVM	50	42.9	21.4	20	20	30.6
	KNN (10)	31.3	31.3	43.8	25	56.3	37.5
	Ensemble	42.9	28.6	14.3	20	46.7	30.6
Skewness	SVM	50	57.1	42.9	13.3	46.7	41.7
	KNN (7)	50	50	42.9	13.3	46.7	40.3
	Ensemble	78.6	57.1	28.6	26.7	60	42.5
Kurtosis	SVM	7.1	28.6	7.1	60	60	31.9
	KNN (4)	37.5	37.5	43.8	37.5	31.3	37.5
	Ensemble	35.7	21.4	7.1	60	26.7	29.2
First quartile	SVM	7.1	7.1	7.1	6.7	66.7	20.8
	KNN (7)	42.9	46.7	28.6	14.3	26.7	31.9
	Ensemble	35.7	28.6	28.6	26.7	60	36.1
Interquartile range	SVM	57.1	7.1	14.3	40	6.7	22.2
	KNN (6)	25	37.5	37.5	62.5	25	37.5
	Ensemble	35.7	28.6	14.3	13.3	20	22.2
Root Mean Square	SVM	64.3	14.3	7.1	26.7	26.7	27.8
	KNN (10)	35.7	28.6	28.6	26.7	60	36.1
	Ensemble	50	42.9	21.4	33.3	26.7	34.7
Power	SVM	100	35.7	7.1	6.7	6.7	27.8
	KNN (5)	25	37.5	37.5	62.5	25	37.5
	Ensemble	42.9	64.3	7.1	6.7	33.3	30.6
Energy	SVM	64.3	7.1	21.4	6.7	66.7	33.3
	KNN (7)	31.3	37.5	50	43.8	12.5	35
	Ensemble	50	42.9	42.9	26.7	26.7	37.5
Nanmean	SVM	57.1	7.1	7.1	20	33.3	25
	KNN (10)	35.7	28.6	28.6	26.7	60	36.1
	Ensemble	42.9	50	28.6	26.7	20	33.3
Harmonic Mean	SVM	35.7	50	7.1	13.3	33.3	26.4
	KNN (8)	56.3	31.3	37.5	37.5	50	42.5
	Ensemble	25	43.8	31.3	43.8	75	43.8
Trimmean	SVM	50	28.6	21.4	6.7	6.7	20.8
	KNN (10)	25	37.5	37.5	62.5	25	37.5
	Ensemble	42.9	42.9	21.4	40	33.3	36.1

The highest accuracy are in bold

Table 6 Performance on combined classes before PCA

Performance of Hypovigilance features after fusion without PCA						
Classifier	Normal (%)	Drowsy (%)	Fatigue (%)	Visual (%)	Cognitive (%)	Average (%)
SVM	85.7	42.9	21.4	13.3	53.3	43.1
KNN (10)	64.3	57.1	50	33.3	26.7	45.8
Ensemble	92.9	64.3	42.9	20	66.7	56.9

Table 7 Performance on combined classes after PCA

Performance of Hypovigilance features after fusion with PCA						
Classifier	Normal (%)	Drowsy (%)	Fatigue (%)	Visual (%)	Cognitive (%)	Average (%)
SVM	64.3	50	42.9	6.7	60	44.4
KNN (10)	57.1	64.3	35.7	33.3	53.3	48.6
Ensemble	64.3	71.4	50	33.3	73.3	**58.3**

The highest accuracy are in bold

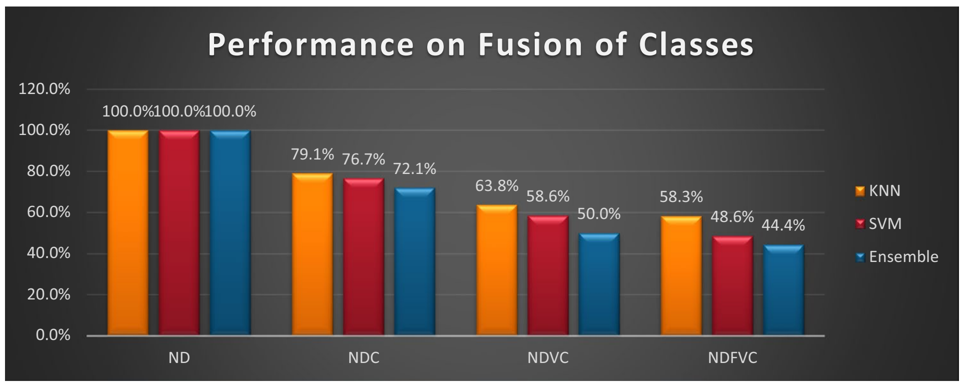

Fig. 9 Comparison on performance with fusion of classes. *N* normal, *D* drowsy, *F* fatigue, *V* visual inattention, *C* cognitive inattention

Alert mechanism

The alert mechanism can be installed in a vehicle through various modalities namely visual, auditory, vibration and others. The developed algorithm can be integrated into the existing accessories of the car for efficient and optimal implementation. Increasing the luminance and flashing of lights inside the car, an increasing sound alarm or vibration sensor in steering wheel or seat belt can also be used to alert the driver [35]. Instruction can also be given to the driver on what he can do to keep him/her alert. The various alert mechanism can also be integrated with GPS, smart phones and other wearable smart devices [36]. Advanced alert systems can also include measures to slow down the vehicle or switch on the park lights so that the nearby vehicles will get some sort of indication to be careful.

Real time implementation

Implementing the developed algorithm in real time and installing the same into a vehicle is an integral part of ADAS. This would require an appropriate and economical way of acquiring the ECG data, processing them and alerting the driver on time before a mishap occurs. The ECG or HRV data to detect the hypovigilance states of the driver can be obtained using the smart wearable devices like smart watches, smart belts or smart gloves that are readily available in the market [4, 36, 37]. The wide use of smart watches and similar devices in the society makes it easier to not only obtain the data but also to install the developed algorithm with the existing systems.

Nowadays, cars and other automobiles in the market are mostly internet enabled and has an Android or iOS system installed. They also come up with a number of smart features such as vehicle tracking, air quality checks, driver assistance etc. The hypovigilance detection algorithm can be integrated into smart devices which in turn can be made available along with the existing smart features and interfaces in the car. Similarly, the alert mechanism can also be installed into the existing accessories of the car such as lights on the roof console, stereo, steering wheel or seat belt [37].

As the entire system will be installed into the existing hardware of the vehicle, the cost of implementing in real time would not be high. The ECG data can also be acquired using smart wearable watch or other devices.

Conclusion

The work on the detection of driver hypovigilance (drowsiness, fatigue, visual inattention and cognitive inattention) using physiological signals from ECG has concluded that two-class detection gives better accuracy when compared to the fusion of five class detection. From the two-class classifier result, Ensemble with ANOVA selected features performs better in detecting normal–drowsy, normal–visual inattention, normal–fatigue and normal–cognitive inattention with the classification accuracy of 100%, 93.1%, 96.6% and 96.6% respectively. The five-class fusion algorithm provides an overall accuracy of 58.3%. To improve the accuracy frequency domain features can be extracted. Along with the ECG performance, other physiological signals can also be combined to improve the detection accuracy for hypovigilance. In future, vehicle-based and behavioural method can be combined with physiological methods so that a reliable system can be developed. A wearable wireless device can be developed based on the combined implementation of hybrid method in detecting driver's state.

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Compliance with ethical standards

Conflict of interest The authors of this paper have no conflict of interest to disclose.

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