Detection of Driver's Drowsiness Using New Features Extracted From HRV Signal

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Abstract

As we may find in news related to road fatalities, we see more or less one third of these fatalities are because of drowsy driving or fatigue of drivers. Many researchers had investigations in detection of drowsiness of the drivers using biological signals e.g. ECG, EEG, EOG and image processing of drivers' faces or information shows how driving is going on. Using HRV signal extracted from one lead ECG or pulse oximetry signal is very simple and easy, but almost in all of these researches common features like time and frequency features and nonlinear features have been used. In this study, we used common features extracted from new signals in addition to features extracted directly from HRV. We first extracted HRV signal from ECG and then we construct Poincare map. From Poincare map we extracted two new signals. From these new signals we extracted some frequency and nonlinear features and then we used normal classifiers and reached to a higher sensitivity than before. Sensitivity up to 85% is usual in recent papers. We reached to a sensitivity 91.5 when we used selected features from both HRV and New signals.

Keywords: Drowsiness detection, electrocardiogram, ECG, Heart Rate, New features

1. Introduction

This paper investigates the use of new features extracted from HRV signal. In the United States alone, drowsy driving causes more than 83,000 crashes a year and contributes to over 1,000 deaths [1]. Drowsiness can be a result of either lack of sleep or a sleep disorder, such as narcolepsy. Recent work has focused on the development of technologies to detect drowsiness while driving based on various physiological parameters such as heart rate, respiration rate, posture, rapid eye movement and head movement of the driver [3]. Heart rate variability analysis of the driver has also been useful in sensing drowsiness [5] [4]. Researchers have investigated using an electroencephalography(EEG) sensor to monitor the driver's brain activity [11] and image processing of video of the driver [7] to detect the driver's drowsiness state.
In this work, the heart rate and heart rate variability new features are used to distinguish between the awake and sleep/drowsy states. We want to earn Phase and magnitude from HRV and extract features from new signal. Also, our approaches are validated against ECG obtained data from the physio Bank [2] and the result are summarized.

2. Background

A small electric pulse initiates a heartbeat and triggers a contraction of the heart muscle. These electrical signals can be detected using electrodes attached to the surface of the skin or within a small distance of the skin using ECG devices. An ECG signal is a representation of the heart 's electrical activity at different stages of the blood flow in the heart. Each cardiac cycle produces ECG waves designated as P,Q , R, S and T to represent different phases of a heartbeat. The R-R interval refers to the interval from the peak of one QRS complex to the peak of the next in an electrocardiogram.

A. Heart Rate

Heart rate is the number of heartbeats per unit of time, expressed as beats per minute(bpm). It can be calculated using the R-R interval from an ECG sensor, by inverting the R-R interval (unit in seconds) and multiplying by 60. Alternatively, the rate can be established by counting the number of QRS complexes in a 10 second interval and multiplying by6.

B. Heart Rate Variability Analysis

Heart rate variability (HRV) is the beat-to-beat variation in the heart rhythm as seen in the variation of the R-R intervals in an ECG sample [8][9]. A Power spectrum density(PSD) estimate is calculated from the R-R intervals using fast Fourier transformation(FFT), and the PSD is divided into frequency bands: the very low frequency (VLF,0-0.04 HZ), low frequency (LF,0.04-0.15 HZ), and high frequency (HF,0.15-0.4HZ). The ratio of LF to HF power, SDSD, SDNN, RMSSD, PNN50 ، PNN20, Tinn, DFA, Tri, Cdim, apen, sd1, sd2 ، sd1/sd2 are features that we want to use in detection of driver's drowsiness.

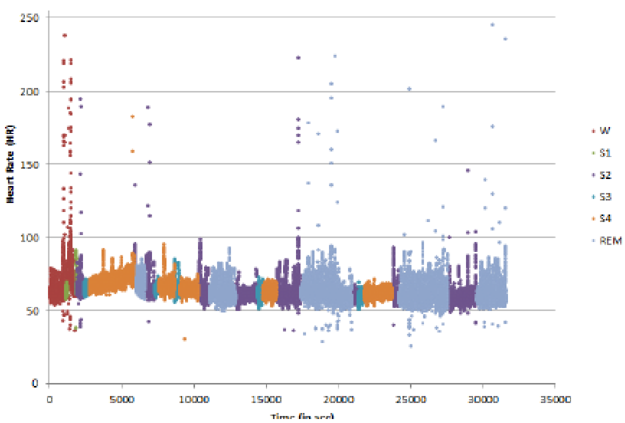
In previous studies, HRV analysis has shown a difference between waking and sleep states [10], with the LF-HF ratio decreasing as a person becomes sleepy [9] [3] [4] [5].

3. Data Set

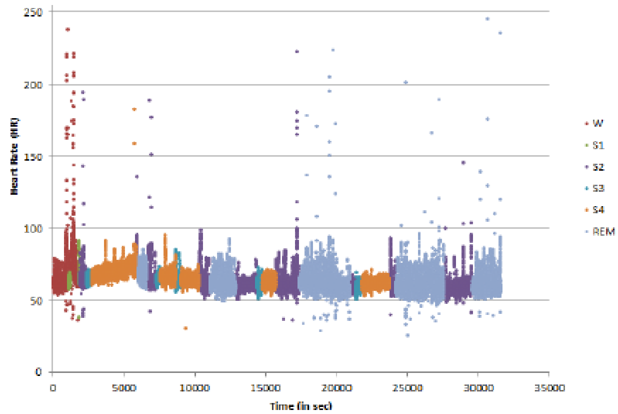
Actual sleep and waking driving data was used to test the system. Specifically, our analysis is performed on annotated data from databases available at the physio Net website [6]. physio Net offers large collections of recorded physiologic signals called physio Bank datasets, freely available to users.

CAP Sleep Database

The database used is the cyclic Alternating Pattern (CAP) sleep database. Each record in the database includes three or more ECG signals with sleep stage annotations [10]. The database includes records with various types of sleep pathologies, of which the "No Pathology" and "Narcolepsy" records were selected for our work. One record from each type of recording has been represented in Figure 1 (a) and (b). The graphs are color coded according to the sleep stages and awake stage.



(a)



(b)

Figure 1. Graphs of Heart Rate Data Including (a) Heart Rate for normal Sleeping Data (b) Heart Rate for Narcolepsy Data

3.1 Data Processing Method

First we used a notch filter to suppress the line artifact. Then we applied an average filter to smooth the signal. Now we can use a simple threshold method to detect the R-waves. We used 45% of the maximum of the signal as a fixed threshold. However, we could use Pan Tomkins Method for R-wave detection.
Then we extracted RR intervals as our HRV signal.

4.Techniques & Methods:

4-1 Time domain features

Time domain Features were extracted from R-R interval ECG signal are including SDNN: standard deviation of the NN (R-R) intervals

NN50: The number of pairs of successive NN (R-R) intervals that differ by more than 50 MS

PNN50: The proportion of NN50 divided by the total number of NN(R-R) intervals

RMSSD: Root mean square of the Autonomic nervous system's parasympathetic branch and is the basis of our HRV score.

SENN: Standard error or standard error from mean

SDSD: Standard deviation of difference between R-R intervals

SDNN: Standard deviation of R-R intervals

4-2 Geometrical feature:

The series of R-R intervals can also be converted into a geometric Patten, such as the sample density distribution of R-R interval durations. The triangular interpolation of RR interval histogram (TINN) is the baseline width of the distribution measured as a base of a triangle, approximating the RR interval distribution. The advantage of using geometric methods is non susceptibility to quality analyses R-R interval.

4-3 Non-linear feature:

Detrended fluctuation analysis is a technique that consist of nonlinear- dynamics. In this graph each space from RR interval is designed as previous space. This graph with calculating SD from y=x, y=x+2R-R_m, that R-R_m is mean of R-R(i). SD1 and SD2 are parameters that is extracted from Detrended fluctuation graph. We use SD1/SD2 for detection of drowsiness.

4-4 Frequency domain features:

Frequency domain methods usually involve the following three steps.

1- Resample the RR interval signals and linear interpolation.
2- Estimate the power spectral density (PSD) of the RR interval signal by using FFT.
3- Compute frequency domain parameters from the PSD.

4-5 Feature extraction and selection:

We extracted common features e.g. time feature, frequency features and nonlinear features from HRV signals.

The second step was to produce the new signals. We constructed Poincare Plot and then we calculated the magnitude and phase of each point sequentially. These new signals can be used for extracting the mentioned features. So we have two kinds of features: features from HRV signal and features from these new signals. The number of extracted features was 66. Now we have too many features and we can reduce the numbers of the features by many methods. We used t-test to select some features. We now have 18 features to apply them to our classifier. The results of selected features are shown in Table1.

4-6 Classifier:

We used a MLP neural network as our classifier. It contained 5 hidden layers. We used 80% of the data for training and 15% for validation and 5% for test.

5. Results

After using the classifier, we counted TP, FP, TN and FN. Then we got the sensitivity, specificity and accuracy by the following formulas:

Sensitivity=TP/(TP+FN)
Specificity=TN/(TN+FP)
Accuracy=(TP+TN)/(TP+TN+FP+FN)
The results are shown in Table 2,3.

Table1: Selected features after T-test for HRV and new signals

Features	HRV Signal	New signals	
		phase	magnitude
SDSD			
SDNN			
RMSSD			■
Mean(HRV_NNx)			
Mean (pnn50)		■	
Mean TRI			■
Mean TINN			
Mean tri		■	
Mean Tinn		■	
Mean (Alpha)			
Mean (Cdim)	■		■
Mean (pLF)	■		■
Mean (PHF)			■
Mean(LFHF ratio)			■
Mean (VLF)			
Mean (LF)	■		■
Mean (HF)	■		■
Mean (SD1)	■		■
Mean (SD2)			
Mean(SD1 SD2 ratio)			■
Mean (average)			
Number of features	5	13	

Table 2: Sensitivity, specificity and accuracy from HRV signal

Features	Sensitivity	Specificity	Accuracy
Selected Features	88.4	88.2	88.3

Table 3: Sensitivity, specificity and accuracy from HRV and new signals

Features	Sensitivity	Specificity	Accuracy
Selected Features	91.5	91.3	91.4

6. Conclusion

We compared results of accuracy, sensitivity and specificity from HRV signal with HRV and new signals. The value of accuracy, sensitivity, and specificity of HRV and new signals is more than HRV signal. The number of selected features after T-test for HRV and new signals is more than HRV signal. So, this method is an appropriate method for detection of driver's drowsiness.

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