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Driver's Drowsiness Level Detection Using Heart Variability Rate from Wearable Devices

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ABSTRACT
The goal of this research is to determine which classification model is optimal and accurate to detect the state of drowsiness of automobile drivers by utilising features from Heart Rate Variability (HRV) of Electrocardiogram (ECG) signal from wearable devices. Methods used are feature selection of HRV for classification utilizing Support Vector Machine (SVM) with linear and with Radial Based Function (RBF) kernel, K Nearest Neigbors (KNN) and RBF Neural Network (RBF NN). SVM with RBF kernel gives better accuracy for almost every feature selected with margin above 20% than SVM linear, while both method also give accuracy result better than with KNN or RBF NN. We conclude that based on this comparison, SVM with RBF kernel is the best method for this classification.

Keywords: Electrocardiogram, Heart Rate Variability, Vehicle Safety, Drowsiness.

1. INTRODUCTION

1.1 Background

Several research reveal that road accident as a direct result of drowsiness can be as much as 10 to 30%. Data from NHTSA (nhtsa.gov) states that 795 loss of life in year 2017 as direct result of drowsy driving. Between 2013 and 2017, there are 4111 fatal accidents involving sleepy driver of motorized vehicle. In total the number of sleepy driving causing accident in 2017 is 91000 occurrences. (https://www.nhtsa.gov/risky-driving/drowsy-driving)

According to AAA Foundation, one out of ten accident is caused by drowsy driver so that sleepy driving is a much bigger problem than we previously perceived. Lack of sleep then driving creating bigger risks to all road users. More than 3500 accidents or 9,5% of them were caused by sleepy driver behind the wheel in United States between October 2010 and December 2013 and involve int 700 accidents. Other than causing loss of life, driving while drowsy also causing property damages.

The physical condition of the driver with a high level of fatigue and tend to withstand drowsiness has the potential to cause danger to himself and other road users. Data from the National Police Headquarter said that 65.67% of traffic accidents were caused by human error, one of which was drowsiness.

Drowsiness affects physiological signs that can be detected and measured. One physiological sign that we can detect and measure is data of rhythm of the heart beat, especially the HRV which is known to have close relation to state of awake or drowsy.[1]–[3]

1.2 Problem Identification

Driving is part of modern human life. Because of that driving safely becomes a very important thing in everyday life. Even though there are other aspects of safety development, such as passenger cabin security, repairs to safety belts and air bags, the incidence of serious accidents has also increased. Thus we need to focus more on preventing accidents, especially accidents that occur due to sleepiness.

Therefore, a mechanism is needed to warn the driver of the situation. Heart rate monitoring can already be done by a wearable device that can be used comfortably and does not interfere with driver activity. By processing data from these devices, we can create an early warning system about the driver's level of fatigue or drowsiness.

1.3 Objective and Purpose

Detection of the state of awake or drowsy can be done in various ways using the results of several studies. A more accurate technique is based on the phenomenon of physiological signs from brain waves or heart rate.

We can detect the fluctuations of heart rate using devices that can be wear naturally and not interfering with the driver. Some unobtrusive wearable devices can be used to detect cardiac activity, such as watch-like Blood Pressure device [4], ECG necklaces for monitoring the heart in longer terms[5], eyeglass-like device for measuring PTT and heart rate[6], h-Shirt to measure BP and heart rate [7], a ring-type device linked to mobile device for heart rate measurement [8].

We can use cardiac activity monitoring from wearable devices that can be used to detect the level of driver fatigue and later can be developed an early warning and detection system that will provide a warning to the driver or related parts regarding the driver's fatigue status to be followed up by instructing the driver to rest or change the driver.

1.4Scope

The scope of this research is to test the method of detecting variability of heart rate from recorded data obtained from wearable devices, to ensure the detection of levels of drowsiness that are harmful to the driver in continuing his duty.

We used data from is Jennifer Healey's [9]research which was donated to Physionet[10]. This data contains a collection of records of several parameters of healthy volunteering drivers taken during which they are driving automobile along a predetermined course that includes city roads and highways within Boston and around the city, Massachusetts. This study was to examine the possibility of recognizing levels of fatigue based on recorded signals. In this study ECG data from the study will be used. The level of fatigue measured from HRV from the ECG data uses a definition of the results of previous studies that have proven the link between HRV and the level of fatigue. This study will demonstrate the use of data obtained from devices that can be used to provide warnings or notifications so that the driver rests at the right time.

2. RELATED WORKS

2.1Heart Rate Variability (HRV) and Heart Rate (HR)

Heart is a human vital organ located in the chest cavity, between the two lungs, behind the sternum and costal cartilage that connects the sternum and ribs. The heart's job is to pump blood throughout the body to distribute oxygen-rich blood to the body's organs and carry blood from the organs back to the heart. The heart works like a pump, but works involuntary, it cannot be consciously controlled by the owner, but instead it is regulated by the Autonomous Nervous System (ANS). In our brain, the ANS is regulated by the hypothalamus. It is in this kind of activity and autonomic rules life vasomotor reflexes as vomiting, coughing, swallowing and sneezing. The movement of the heart that contracts to pump blood is regulated by pacemaker cells (modified cardiomyocytes) that can independently create signals that regulate the potential rhythmically. Measurement of HR and HRV will involve notations used in depictions of heart rhythms through an ECG (Electrocardiogram). Normal heart rhythm is sinus rhythm that is originated from impulses triggered by SA nodes which is located close to the orifice of the Superior Vena Cava located in the heart’s right atrium. The sinus rhythm is a rhythm in which there is a P wave trailed by a Q-R-S complex. Heart rhythm must also be regular, meaning that the distance between the same waves is relatively the same and regular with small variations.

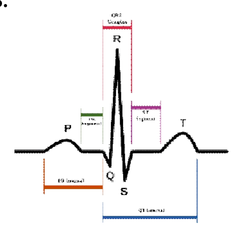

Figure 1: Schematic depiction of a normal ECG cycle

Figure 1describe one heartbeat as measured and plot by ECG machine. The distance between one R wave and the R wave from the next beat will always be approximately the same and regular. In the image, ECG results can be noted the existence of so-called sine waves, namely the existence of P waves, which are then always followed by the QRS complex.

Heart Rate is a number of how many beats in minutes the heart is beating and measured in units of beats per minute (beat per minute - BPM) whose numbers will always change with heart rate. Heart Rate Variability (HRV) is degree of the variation or variability in time unit between two successive heart beats[11].

HRV provides a measurable indication of neuro cardiac function and is produced by the interaction of the heart and brain and the Autonomous Nervous System (ANS)dynamic non-linear processes. The variability is an attribute arises from an mutually supporting regulatory system, which operates on dissimilar time measures to help our bodies familiarize to conditions of environment and emotional. HRV mirrors the parameters of autonomic balance, BP, respiratory, bowels, and venal tone, which always related to the width of the blood vessels that control blood pressure.

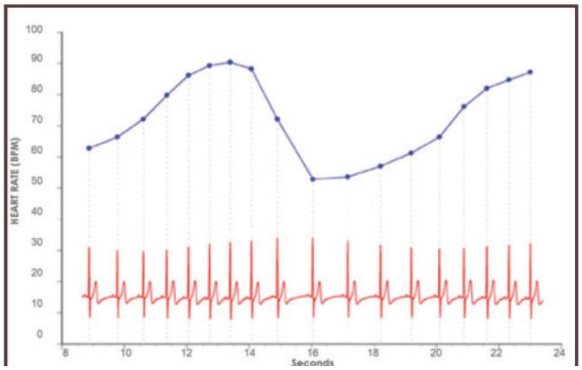

Figure 2: Comparison of heart rate with heartbeat duration.

In the Figure 2 the red line at the bottom shows the electrocardiogram (ECG), and the blue one is the graph of the number of pulses when it is drawn. The interval of the time between two heartbeats on seconds 0 and 13 changes to be shorter and the heart rate increasingly become faster and begin slowing down around the 13th seconds. This heart rhythm changes create pattern of slowing and quickening of heart rate.

2.2 HRV feature classifications

HRV is describable in time domain and frequency domain within 24 hours, short term (ST, Short Term, ~ 5 minutes) or even more ultra-short-term (UST, <5 minutes). Long-term measurements are more representative to describe processes with slow fluctuations, such as circadian rhythms and the cardiovascular system response to environmental condition and workloads of the person.

The HRV index in time domain measures how much change in inter-beat intervals (IBI), which is the period between two heartbeats, usually expressed also as NN or RR, i.e. two R peaks interval, or the interval between two normal ECG cycles which is generally interchangeable. These values are utilizing unique units or within the natural logarithm of the initial units to urge a ordinary dissemination of values[12]. NN interval, an interbeat interval that no longer contains artifacts; RR interval, the interbeat interval between successive heartbeats[11].

The R-R interval is calculated from ECG recording data using the modified R peak detection method made by Pan-Tomkins[13]. IBI is the time interval from the two recorded R peaks.

Table 1: Features of HRV in the time domain

Feature	**Unit**	**Explanation**
SDNN or SDRR	ms	This is the Standard Deviation of NN Interval $\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(RR_i - RR)^2}$ (1)
SDANN	ms	This is Standard Deviation from Average value of NN Interval that is calculated per 5-minute segment instead of using the entire 24-hour series [11].
SDNNI	ms	Standard Deviation of NN Interval is average value of the standard deviation of all interval RR for every 5 minute segment of 24-hour HRV records. $\boldsymbol{SDNNI} = \sqrt{\sum_{i=1}^{n-1}\frac{(RR_i - RR)^2}{n-1}}$ (2) SDNNI correlates with VLF strength for 24 hours.
pNN50	%	$P\,(\lvert RR_{i+1} - RR_i \rvert > 50ms)$(3) PNN50 is strongly associated with PNS activities [14]. This directly correlates with the power of RMSSD and HF.
HR Max – HR Min	bpm	The normal distinction between the most elevated and least HR amid each cycle (HR Max - HR Min) and is exceptionally touchy to the impacts of breath rate and autonomous of vagus nerve activity. At slightest a 2-minute test is required to compute HR Max - HR Min.
RMSSD	ms	$\boldsymbol{RMSSD} = \sqrt{\frac{\sum_{i=1}^{n-1}(RR_{i+1} - RR)^2}{n-1}}$ (4) RMSSD indicates beatto beat deviations in HR and is the essential in time domain utilized to appraise vagally interceded changes reflected in HRV [15]. Twenty-four hours of RMSSD estimations are closely related to values of HF and pNN50[16].
TINN	ms	The width of the histogram base line that displays the NN interval [17]. But its value can be significantly distorted only by contamination of two artifacts in a 5-minute section, such as SDNN and RMSSD [12].

Frequency domain measurements offer estimates of the spread of powers, absolutely or relatively, of the four frequency bands. The Joint Task Force of the European Society of Cardiologyand theNorth American Society of Pacing and Electrophysiology(NASPE)defined waves of the heartbeat into four frequency bands, i.e. Ultra Low Frequency (ULF) (lower than 0.003 Hz), Very Low Frequency (VLF) (between 0.003 and 0.04 Hz), Low Frequency (LF) (between 0.04 and 0.15 Hz), and High Frequency (HF) (between 0.15 and 0.4 Hz).

Table 2: Frequency domain HRV Features

Feature	Unit	Explanation
LF/HF	%	LF-HF ratio
ULF Power	ms^2	ULF band absolute power
VLF Power	ms^2	VLF band absolute power
LF Power	ms^2	LF band absolute power
LF Power	%	LF band relative power
LF Power	sn	LF band relative power in normal units
LF Peak	Hz	LF band peak frequency
HF Power	ms^2	HF band absolute power
HF Power	%	HF band relative power
HF Power	sn	HF band relative power in normal units
HF Peak	Hz	HF band peak frequencies

Power defines the signal of the frequency band energy measured. This measurements is described in relative or absolute power. Relative power is an estimate value in percentage from total HRV power or expressed in normal unit (sn). Absolute power is expressed in ms^2 / Hz, a division of the absolute power from a particular band of frequency and the total sum of absolute powers from HF and LF bands. Features in this domain lets us make a direct comparison in measurements of the frequency domain of the two even if there is a large variability in specific band strength to the total power among healthy individuals whose age is grouped[18].

In healthy humans, we can find a dynamic relationship between Sympathetic Nervous System (SNS) and Parasympathetic Nervous System (PNS)that controlling heart movements. PNS controls when we are resting, where the average HR is at 75 bpm. HR can be slowed down to 20-30 bpm, or even stop it briefly by PNS[19]. The power ratio of LF to HF is often referred as one measure of sympathetic-parasympathetic balance. In previous researches, the analysis of HRV showed the difference between fully awake and drowsy state[20][21]. Some research found that ratio of LF/HF declines when the person enter drowsy state, therefore can be one effective method to detect the beginning of drowsy state of a driver [22][23][24][25].

2.3 Drowsiness level detection

QRS complex are a dominant feature in non invasive biometric feature without the need to use the whole ECG morphology [26]. Therefore we can focus on detecting the QRS features to detemine the drowsiness level.

Determination of the condition of the level of fatigue will use a radial-based neural network (RBF-NN) function to differentiate awake and drowsy state. The RBF-NN topology structure is depicted in the figure 3[27].

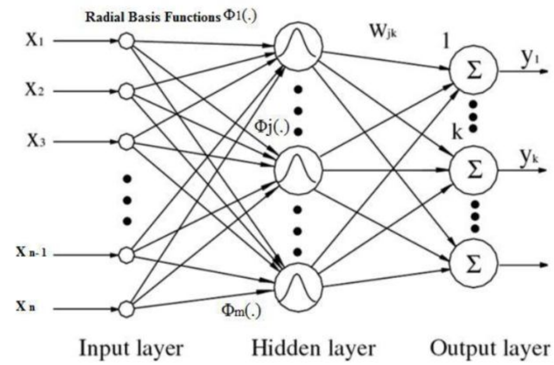

Figure 3: RBF-NN topology structure

The mapping or conversion process from the input layer to the hidden layer in RBF NN is non-linear. The papping from hidden layer to output layer is linear[28].
The output points of the RBF-NN are described in the form of the following mathematical formula:

$$y_i(x) = \sum_{i=1}^{k} \omega_{jk} \left|\left|x - \mu_i\right|\right|;\ \sigma_i \qquad (2)$$

RBF-NN input is the *x*. The $y_i(x)$ is the function relating output to *j*. The combination of y_i and μ_i is linear to the central neuron. Also linear to the bandwidth of the neuron σ_i, the amount of neurons k and to the radial-basis function Φ(). Weight of class *j* vector is written as ω_j and ω_{ji} is the weight of center*i*-th and class *j*-th. The RBF-NN is using Gaussian function as base. The K-Means method determine the center of neurons from RBF-NN.

The K-Means method is used when grouping a dataset into groups, as many as K pieces. The K value is the initial number, where the algorithm will find the best clustering. Determination of the K number at the beginning of this step is also very crucial in the process of clustering. The results of the K-Means clustering will be used as input from the RBF-NN.

This results are to be compared to the result from classification using K Nearest Neigbor (KNN) using several values of *k*, and Support Vector Machine with linear and RBF kernel.SVM classification major characteristic is the ability to select multiple kernel functions[41]. Frequently used are Radial Basic Function (RBF), Linear, polynomial, and sigmoid. Here we used linear and RBF [42].

2.4Classification accuracy measurement

Classification performance of normal or fatigue conditions will be tested by computing the accuracy, defined as ratio of the number correctly classified data to the total number of data classified. With True Positive (TP), False Positive (FP),True Negative (TN), and False Negative (FN), the performance of this classification can be written as the following formula[29]:

Accuracy= ((TP+TN))/(TP+TN+FP+FN) ×100%

3. RESEARCH METHOD

3.1 Framework and Research Steps

The steps taken for this research is as described in Figure 4. We start with pre-processing the data to get the IBI data, then we filter the noise and normalize it before we start with the analysis. Analysis begin with extracting the HR features intime and frequency domains. Then we classified the data in order to get the result of drowsy or awake condition.

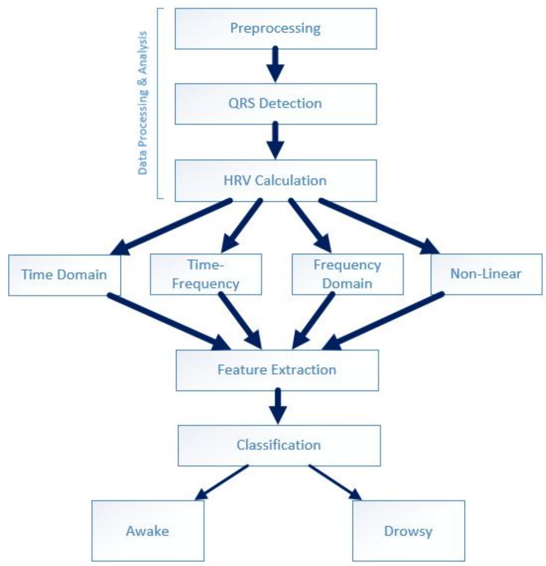

Figure 4: Research steps

3.2Data Collection

The data used in this study uses data collected by Jennifer Healey in Physionet databank and contains a collection of records of several measurements of healthy person volunteering while driving on routes around Boston [30]. This study purpose was to investigate the possibility of recognizing fatigue levels based on recorded signals, which included ECG, EMG (right trapezius), respiratory system, galvanic skin resistance (GSR) on hand and feet. This research will only use the ECG part of the data.

3.3 HRV Data Extraction

ECG signal normally gets noise or even corrupted cause by several kind of artifacts and noises. The noise can come from electrode contact, interference from power lines, motion artifacts, baseline drift, contraction, and instrumentation noise from nearby electronics apparatuses.[31]

We begin with preprocessing data where we filter the signals from all sort of noises using a (5) band-pass filter, to reduce muscle noise, power line interference, errors due to movement and T-wave interference.

In addition, the IBI data samples are taken unevenly and this requires re-sampling because the signal must have a unvarying sample each time we apply the spectral analysis using the transformed domain approach [32].

HRV data is then extracted in time and frequency domains. Time domain features are Mean, RMSSD, pNN50, and SDNN.Frequency domain features using LF and HF, mainly for computing ratio of LF/HF.

The IBI is calculated from ECG recording data using the modified R peak detection method made by Pan-Tomkins[13] and improved by [33]. Then these IBI are grouped into time segments per 5 minutes.

The LF band is at the frequency of 0.04 to 0.15 Hz describes cardiac activity sympathetically and para-sympathetically[34]. The HF frequency band describes only the parasympathetic activity[34][35]. To get the value of the LF and HF of HRV, we are utilizing a Fast Fourier Transform (FFT)to obtain the interval power spectral density (PSD)[36]. Measurements of spectral power values are in absolute values (aHF, aLF, aVLF), and the percentage of the sum (pLF, pHF)of values aLF and aHF [37].

To classify between awake and drowsy, we will use KNN with several values of *k*, SVM using a linear kernel, and SVM using an RBF kernel. RBF-NN is also used to distinguish between awake and drowsy conditions, as stated above.

3.4 Proposed Method for Drowsiness Level Detection

Signal ECG obtained, we detect the peak signal R using a Pan-Tompkins algorithm with an improved technique [33]. After obtaining all the R signal data the calculation of the interval between the two peaks is carried out and the results are made correlated with the time of occurrence, to obtain data if two peaks occur at t1 and t2, then the result is the point p, i.e. (t2-t1, t2).

Several algorithms for cleaning outline and noise data are needed. Because HRV data that is formed can have very high peaks which are identified as data relating to the etopic beat[38]. Because ectopic beats are not controlled by ANS, they need to be cleaned. There are two methods that can be run to eliminate data relates to ectopic beats, called pctChg, which classifies IBIs as outliers if the values differ by more than 30% from the average of four previously accepted intervals[39]. This method detects better than the second method, namely std Method [40].

Using data that has been cleared from outliers, we can calculate HRV movements and use the results presented by[3], we use the HRV range in episodes of high fatigue, i.e. (3.61 ± 2.93 to 1.2 ± 0.87) as an area to trigger a driver fatigue warning level and use it as a trigger for an action. We will use annotated ECG data from CAP database from physionet to train the classifier.

To determine the classification performance we calculate the accuracy of the classification. Using definition above, the accuracy is the ratio of correctly classified and the total of classified data. From the existing dataset, we already know which data set contains the data when the driver enters the fatigue level. The data has been annotated from previous research using CAP dataset from physionet. From these annotations we can determine the level of classification accuracy that we do. From each group of data we previously grouped in 5 minutes, we will make a comparison of the detection accuracy for each of these features selected.

4. RESULTS AND DISCUSSION

Seventeen ECG records is obtained from phyisionet databank with duration varies between 1 hour and 6 minutes to 1 hour and 23 minutes. The RR-interval data is divided in 5 minutes segment each then we extract the HRV features. We then extract the time domain features, Mean, RMSSD, SDNN, pNN50, NN50 and TINN and features in domain frequency HF and LF.

Table 3: Measurement of accuracy of classification of drowsiness levels

Accuracy (%)	KNN 1	KNN 2	KNN 3	KNN 5	SVM-Linear	SVM-RBF	RBF
Time	51.6	51.0	60.8	48.6	18.3	71.5	61.1
Frequency	74.8	48.7	52.6	70.6	52.7	74.5	42.0
Non Linear	69.7	50.8	77.3	42.9	58.7	**87.9**	47.7
Poincare	36.8	49.6	39.9	53.6	62.6	87.0	71.8
Wavelet	59.3	54.8	23.8	69.9	83.3	78.5	61.1
STFT	38.3	75.0	58.0	48.5	65.0	21.1	34.9

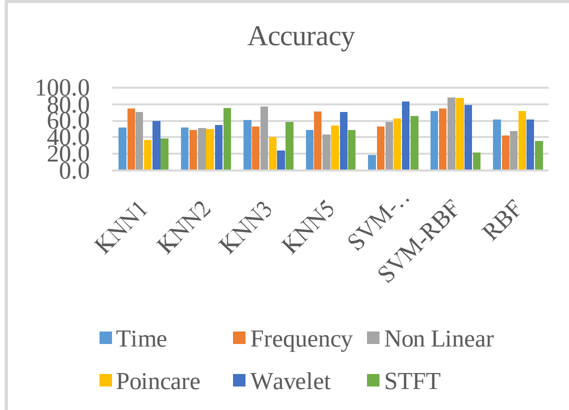

Figure 5: Accuracy of classification

Time-domain HRV analysis results for KNN were indifferent for k value 1, 2, 3 and 5. While STFT analysis for k=1 show low value, for k=2 is higher. However, with *k*=3 and *k*=5, the STFT result is decreasing. Non linear analysis is showing very different result for each classifier, but achieve best accuracy with SVM-RBF at 87.9%.

Classifying with SVM using linear kernel shows lower accuracy compared to the result from using RBF kernel, although not for all features.

5. CONCLUSION

The Inter Beat Interval (IBI) is calculated using modified Pan-Tomkins method. The IBI data is segmented into 5 minutes segments before extracting the features. KNN with value of *k*= 1,2,3, and 5, SVM using a linear kernel, SVM using an RBF kernel and RBF neural network is used to distinguish state of drowsiness and awake. In order to get accurate classification, some parameters are determined during process of training using annotated data from physionet Cyclic Alternating Pattern (CAP) databases. The classification performance is measured by computing the accuracy. Table 3 presents the accuracy of the detection for each classifiers and each features. Detection using SVM with an RBF kernel provides better accuracy compared to other methods used here.

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