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Drowsiness detection using heart rate variability analysis based on microcontroller unit

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Abstract. Drowsiness is one of the main cause of road accidents. Recently, drowsiness detection of driver based on biosignal like electrocardiogram is being studied. Alterations during drowsiness, fatigue, and stress of the driver can be obtained from heart rate variability (HRV). HRV is derived from interval of RR in electrocardiogram. In this article, we present drowsiness detection using HRV analysis based on microcontroller unit. Electrocardiogram signal is obtained by AD8232 module and processed in microcontroller unit. Electrocardiogram is recorded during the subject using driving simulator. We extract features from HRV and use radial basis function neural network to classify between drowsy and normal.

1. Introduction
Each year, over 1.2 million people die on the world’s road, and between 20 and 50 million suffer non-fatal injuries [1]. The epidemic of this road traffic accident is still increasing in most regions of the world. Low-income and middle-income countries have higher road traffic fatality rates than high-income countries. The road fatality rates of low-income and middle-income countries are 24.1 and 18.4 per 100,000 population, respectively. The road fatality rates of high-income countries is 9.2 per 100,000 population. While the road fatality rates of global road are 17.4 per 100,000 [2]. One of major cause of accidents in particular road transportation is drowsiness [3]. Therefore, drowsiness detection is important task in road transportation to reduce the road accident.

Different methods have been investigated for drowsiness detection, including physiological measurements monitoring based on wearable sensor, facial and eye detection with computer vision algorithm [4]. There are three techniques or measures have been developed and used to monitor and detect the driver’s drowsiness [5]. The first measure is vehicle-based measures that monitor how the vehicle is driven. The second is behavioral measures that detect the movement of driver’s face, including eye closure and blinking, head position, and yawning. The third is physiological measures that measure the physiological changes from bio signal.

Since he correlation between sleep rhythm with brain and heart activities is strong, physiological bio signals can give accurate detection of drowsiness [6]. One of these physiological bio signals is electrocardiogram (ECG). ECG represents electrical activity of the heart that can be sampled by placing some electrodes on surface of the body. Some approaches have been conducted to detect drowsiness by ECG. Takalokastari et.al distinguishes drowsy and awake based on R-R interval of
ECG [7]. It shows that the RR-interval is shorter and wider for awake subject than drowsy subject.
Chowdhury et al. recognize and detect drowsiness based on Heart Rate Variability (HRV) analysis [8].
Tjoelleng et al. classify drivers based on artificial neural network (ANN) [9].
In this paper, we present drowsiness detection using heart rate variability. We extract features from
HRV and use radial basis function neural network to classify between drowsy and awake. We use a
real time driving simulator for the project experiment. A driving simulator game is used and played on
personal computer. The ECG is sampled using ECG module, recorded and extracted the HRV feature
in Android Smartphone.

2. Numerical Methods
This paper presents drowsiness detection using heart rate variability analysis based on microcontroller
unit. This section consist of how the data is collected and the proposed method to detect drowsiness
using heart rate variability.

2.1. Data collection
In this subsection, we will describe the participant, equipment, and system design.

2.1.1 Participant and equipment
8 ECG records is obtained from 4 participants. The participant’s average age is 22 years old and the
participants are healthy and had no discomfort on the experiment.

2.1.2 ECG recording system design
An ECG recording system has been developed based on Android Smartphone [10]. ECG recording
system is design to record ECG data from patient. This system consists of an AD8232 ECG module,
microcontroller Arduino Nano, HC-05 Bluetooth module, and Android smartphone. ECG module
records, filter, and amplify ECG signal from the participant. This ECG module has three electrodes
which is placed in the participant body surface.
The ECG signal that is obtained from participant is processed in Arduino Nano. Arduino Nano is a
complete, small, and breadboard-friendly board based on Atmega168. This microcontroller has 14
digital pins that can be used as input or output and 8 analog input/output which provide 10 bits
resolution (1024 different values). Arduino Nano has RX and TX pins to transmit and receive TTL
serial data [11].
The processed ECG signal is sent to Android Smartphone using Bluetooth HC-05. Bluetooth HC-05 is
designed for wireless serial connection [12]. Android smartphone is used for recording the ECG data
and extracting the HRV feature. Figure 1 shows the block diagram of entire system ECG recording
system.

![Figure 1. ECG recording system design](image)

2.2. HRV feature extraction
HRV describes the involuntary nervous function and measures RR-interval variations of an ECG
signal. The feature of the HRV is extracted in Android smartphone. We extract HRV in time domain
(Mean, RMSSD, and SDNN) and frequency domain (LF and HF). The feature extraction is conducted
in some steps. Firstly, R-R intervals are calculated from recorded ECG signal using R-peak detection
based on modified Pan-Tomkins method [13]. RR-interval is time interval of two consecutive R peaks
[14]. Secondly, R-R intervals for each record is segmented in 30 s, 20 s, and 10 s. We calculate R-R
interval and do segmentation in Octave. The final process is the measurement of time and frequency
domain of the HRV. Equation (1) - (3) are used for quantifying Mean, RMSSD, and SDNN, respectively [9]. For frequency analysis, frequency bands for LF is 0.04-0.15 Hz and HF is 0.15-0.4 Hz.

\[
\text{Mean} = \frac{\sum_{i=1}^{n} RR_i}{n} \quad (1)
\]

\[
\text{SDNN} = \sqrt{\frac{\sum_{i=1}^{n} (RR_i - \bar{RR})^2}{n-1}} \quad (2)
\]

\[
\text{RMSSD} = \sqrt{\frac{\sum_{i=1}^{n} (RR_{i+1} - RR_i)^2}{n-1}} \quad (3)
\]

where \( n \) is number of RR-interval, \( RR_i \) is \( i \)-th RR, \( \bar{RR} \) is average of RR-interval.

2.3. Drowsiness classification

We use radial basis function neural network (RBF-NN) to classify between drowsy and normal. The topology structure of RBF-NN is shown in Figure 1. In RBF-NN, the mapping process between input layer and hidden layer is a nonlinear transformation, while the mapping between hidden and output layer is a linear transformation [15].

\[
c_j(x) = \sum_{i=1}^{k} \omega_{ji} \|x - \mu_i\|; \sigma_i \quad (4)
\]

\( x \) is the input of RBF-NN, \( c_j \) is the function related to \( j \)-th output unit (class-\( j \)) and is a linear combination of center of neuron \( \mu_i \), bandwidth of each neuron \( \sigma_i \), total number of neurons \( k \), and radial basis function \( \phi() \). \( \omega_{ji} \) is the weight vector of class-\( j \) and \( \omega_{ji} \) is the weight related to the \( i \)-th center and \( j \)-th class. Gaussian function is utilized as the basis function of RBF-NN. Therefore, the Equation (4) becomes,

\[
c_j(x) = \sum_{i=1}^{k} \omega_{ji} \exp\left(\frac{\|x - \mu_i\|^2}{2 \sigma^2}\right) \quad (5)
\]

We use K-Means algorithm to find the neuron centers of the RBF-NN [16].

2.3. Drowsiness classification performance

Performance of drowsiness classification is determined by calculating the accuracy. To calculate the accuracy, we can use equations following equation,

\[
\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (6)
\]
3. Results and Discussion

8 ECG records is obtained from 4 participant with 10 minutes in duration. We ask the participants to self-evaluate their level of drowsy (LoD). We divide the LoD into two groups, drowsy and normal. The RR-interval is calculated based on modified Pan-Tomkins method. Before we extract the HRV feature, the RR-interval data is segmented each 30, 20, and 10 second. After the RR-interval data is segmented, we extract the time domain (Mean, SDNN, RMSSD) and frequency domain (LF and HF) from HRV. Low Frequency band (LF) has bandwidth 0.04 to 0.15 Hz which describes the sympathetic and parasympathetic activities of the heart activity. High Frequency band (HF) has bandwidth 0.15 to 0.4 Hz which describes only parasympathetic activities of the heart activity. To identify the LF and HF of HRV, RR-interval in time series is used to calculate the power spectral density (PSD) by utilizing Fast Fourier Transform (FFT) [8].

Radial basis function neural network (RBF-NN) is used to classify between drowsy and normal. In order to get the classification accuracy, some parameters are determined by the training process [17]. They are the neuron’s number in hidden layer, the center’s coordinate of each hidden layer, the radius or spread in each dimension, and the weight applied to the RBF-NN.

At the clustering stage, the data is grouped by a certain closeness. Cluster determination will be the neuron centers of the RBF-NN. The number of clusters determines hidden unit that will be used. Data clustering determination can be done randomly or clustering. We use K-Means algorithm to find the neuron centers of the RBF-NN.

Performance of drowsiness classification is determined by calculating the accuracy [18]. Accuracy is the ratio between the number of correctly classified and the total number classified. Table 1 shows accuracy of the drowsiness detection. Drowsiness detection with 30 s segmentation in RR-interval gives best performance among the others.

| Segmentation (s) | Accuracy (%) |
|-----------------|--------------|
| 10              | 76.84        |
| 20              | 78.23        |
| 30              | 79.26        |

4. Conclusion

In this article, we present drowsiness detection using HRV analysis based on microcontroller unit. Electrocardiogram signal is obtained by AD8232 module and processed in microcontroller unit. We use a real time driving simulator for the project experiment. Electrocardiogram is recorded during the subject using driving simulator. We extract features from HRV and use radial basis function neural network to classify between drowsy and normal. Drowsiness detection with 30 s segmentation in RR-interval gives best performance among the others which the accuracy of the drowsiness detection is 79.26%.

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