Drowsiness detection using radial basis function network with electrocardiographic RR interval statistical feature

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Abstract. Drowsiness detection is important since its strong relation with traffic accident. A study for drowsiness level detection using Artificial Neural Network (ANN) method has been conducted. It utilizes electrocardiographic RR interval statistical features and Radial Basis Function Artificial Neural Network or RBF Network as classifier. Drowsiness levels are defined by Karolinska Sleep Scale (KSS) which simplified into two classes, alert and drowsy classes. The main parameter of the RBFN are centers and width which are tuned using k-means clustering. A gradient descent is utilized to determine the output weight. The classifier is evaluated by using DROZY database which are collected from 14 subjects; each of them in different drowsiness levels. Feature extraction stage is conducted by segmenting the 10-min data into 30-seconds and it get the RR interval statistical feature. This study is conducted by varying the number of features as the input of RBFN. The method has been evaluated using 5fold cross validation with best performance 81.96%, 84.77%, 76.90% of accuracy, sensitivity, and specificity respectively.

1. Introduction
Drowsiness has a strong relation with traffic accident since drowsy drivers are considered major causes of it. The World Health Organization reported that road traffic injuries is a leading cause of death globally, more than 1.2 million people die each year on the world’s roads[1]. Therefore, drowsiness detection are important especially in case of drivers to prevent traffic accident and reduce the injury. There are a measurement scales for drowsiness levels, Karolinska Sleep Scale (KSS) is one of the widely known. KSS is a nine level of drowsiness with its equivalent verbal description [2]. There are several types of drowsiness detection, most of them use camera as the main device, but such system may not function well in low ambient luminosity, especially at night when the chances of drowsiness are the highest[2]. While the other method is based on biometric signal. A previous investigation concluded that ECG data is more reliable indicator than the other biometric signal [3]. ECG signal can be utilized to detect drowsiness because of its correlation to the nervous system which control activity of human body including alertness and drowsiness rhythm[4].

This paper shows a study result on detecting drowsiness using electrocardiographic features by artificial neural network as the classifier. ECG signal is a representation of heart electrical activity that produces several kinds of wave, segment, and interval[5]. These ECG waveforms can be utilized as features extracted from ECG. This present study utilizes R-R interval of ECG signal data especially the statistical features of ECG R-R interval. Radial basis function neural network is utilizes in this study to classify whether the ECG data include to alert or drowsy data. Artificial Neural Network is a branch of Artificial intelligence which technique based on the neural structure of the brain and has a learning capability from experiences [6]. R-R interval of ECG signal data features is extracted and become an input information for the neural network. In training stage the neural network recognizing pattern of data, learning from it, then in testing stage the system can recognize and classify new data. In this study 12 kinds of statistical ECG RR interval features are utilize and look for the most optimal features.
2. Numerical Methods

Figure 1. System Main Schema

The main scheme of the drowsiness detection system which developed in this study is showed in Figure 1. This study utilizes database from DROZY database or ULg Multimodality Drowsiness Database. DROZY Database consist of ECG signal from healthy volunteers who performed three successive 10-min psychomotor vigilance tests (PVTs)[7].

Figure 2. (a) feature extraction (b) RBFN classifier
This main scheme begin by firstly extract the ECG feature which differentiate between alert and drowsy data. Radial Basis Function Neural Network is used as classifier algorithm, the RBFN learn to classify data in training stage, so that the system then can differentiate new data into alert or drowsy data in testing stage.

2.1 Feature Extraction
Feature extraction stage is conducted by segmenting the 10-min data into 30-seconds and get the RR interval statistical feature. Feature Extraction stage resulting a differentiator features between alertness and drowsiness data, this study use 12 statistical RR interval features i.e mean, varians, standard deviation, geometric mean, harmonic mean, interquartile, curtosis, skewness, median, mode, maximal, and minimal of ECG RR interval. These features are the input of the Neural Network-based Classifier system model.

2.2 Classifier system design
In the classifier system developed in this study, there are three main processes, namely RBFN training process, testing process, and determining the performance of RBFN that has been established. The steps are shown in figure 2 (b). The RBFN training aims is to determine the parameters in the RBFN i.e. the width and centers of the RBFN activation function and also the weight value of them. At this training stage, 80% of the total ECG data is used, while another 20% is used for testing with 5-fold Cross Validation method. The centers are determine using K-means clustering algorithm. The number of each cluster centers and number of neurons in hidden layer of RBFN is determined firstly. Furthermore, initial values of the each class centers are determined randomly. Then calculating euclidean distance from each data to each cluster centers and updated the clusters center calculate from mean of the members. Then the activation function of every neuron can be obtained from beta coefficient that determine the width of radial basis activation function. The RBFN activation function is:

$$h_j(x) = \phi_j \left( \left\| x - c_j \right\| \right)$$

(2.1)

where

- \( j = 1, 2, \ldots, m \)
- \( c_j = \text{center of } j\text{-nd neuron} \)
- \( m = \text{number of neuron in hidden layer and } \phi_j \text{ is radial basis function} \)

while the RBFN ouput is:

$$y_k(x) = \sum_{j=1}^{m} w_{kj} h_j(x) + w_{k0}$$

(2.2)

where

- \( w_{kj} = \text{weight} \)
- \( w_{k0} = \text{bias term and } m = \text{number of neurons[8]} \).

The next stage after the training is the testing of RBFN. The results of centers, width and weight values obtained from training are used at this ANN testing stage. The testing is conducted to determine the ability of RBFN in detecting drowsiness.

2.3 System Performance evaluation
In the ANN testing phase, also determined the performance of RBFN in sensitivity, specificity and accuracy parameters with the following equation[9]:

- **Sensitivity**
  $$\frac{Tp}{Tp + FN} \times 100\%$$

(2.3)

- **Specificity**
  $$\frac{TN}{TN + FP} \times 100\%$$

(2.4)

- **Accuracy**
  $$\frac{Tp + TN}{Tp + TN + FP + FN} \times 100\%$$

(2.5)
3. Result and Discussion

Results from feature extraction shows that several feature can be utilized to differentiate between alert and drowsy data, but some features are less optimal than others. These feature data pattern is not separated linearly, then to classify the unlinear feature data, Neural network algorithm is used. A system based on RBF Neural network is developed to classify normal and drowsy ECG data. Data results from the Extraction feature stage is used as input to the RBFN classifier. From the system performance evaluation based on cross validation method, obtain results as follows:

Table 1. Accuracy of system results from the 12 kinds of features

| ECG features | Training Accuracy | Testing Accuracy | Detailed information          |
|--------------|-------------------|------------------|-------------------------------|
| f1           | 77.68%            | 63.75%           | Mean of RR interval           |
| f2           | 77.54%            | 64.11%           | Variances of RR interval      |
| f3           | 76.64%            | 64.11%           | Standard deviation of RR interval |
| f4           | 77.90%            | 65.64%           | Geometric mean of RR interval |
| f5           | 78.93%            | 65.89%           | Harmonic mean of RR interval  |
| f6           | 69.33%            | 62.32%           | Interquatile of RR interval   |
| f7           | 75.31%            | 61.06%           | Kurtosis of RR interval       |
| f8           | 73.84%            | 57.68%           | Skewness of RR interval       |
| f9           | 78.61%            | 71.07%           | Median of RR interval         |
| f10          | 73.53%            | 66.61%           | Modus of RR interval          |
| f11          | 77.76%            | 73.93%           | Maximal of RR interval        |
| f12          | 67.01%            | 56.61%           | Minimal of RR interval        |

The result in table 1. shows the training and testing performance of the system with variation of 12 kinds of features. The highest training accuracy is obtained from f9 that is median of RR interval with 78.61% of accuracy, while the less optimal one is f12 the minimal of interval RR with 67.01%. From this training stage, the centers, width, and weight are obtained and utilizes to perform testing RBFN so that the system can classify a new input data whether include to normal or dowsy data.

In the testing process, the system utilizes the center, width and weight from training and classify the new input data. From the table known that the best performance obtained from f11 maximal features of RR interval with 73.39%.

Table 2. Sensitivity and Specificity of system with new input by 12 kinds of features

| ECG features | Sensitivity | Specificity |
|--------------|-------------|-------------|
| f1           | 69.9%       | 54.26%      |
| f2           | 70.21%      | 47.27%      |
| f3           | 78.15%      | 43.06%      |
| f4           | 71.51%      | 54.43%      |
| f5           | 73.74%      | 53.76%      |
| f6           | 73.33%      | 45.68%      |
| f7           | 47.44%      | 47.44%      |
| f8           | 65.65%      | 45.01%      |
| f9           | 80.98%      | 56.67%      |
| f10          | 76.74%      | 51.14%      |
| f11          | 77.78%      | 68.21%      |
| f12          | 75.33%      | 31.72%      |

The other performances parameters shows in table 2 i.e sensitivity and specificity. Sensitivity represent the system ability to detect truly drowsy subject. Otherwise teh specificity represent ability of system to detect alert subjects. Can be concluded that maximal features of RR interval is an optimal features to detect drowsiness which can differentiate data by the system developed. Next, a feature combination is used as input by firstly sorting the single-feature performance results from largest to smallest value. The results of feature combination is shown on table 3.
Table 3. System Accuracy with combination feature input

| Feature Combination | Training Accuracy (%) | Testing Accuracy (%) |
|---------------------|-----------------------|---------------------|
| f11                 | 77.77                 | 73.93               |
| f11, f9             | 88.04                 | 76.78               |
| f11, f9, f10        | 91.12                 | 77.14               |
| f11, f9, f10, f5    | 90.4                  | 79.11               |
| f11, f9, f10, f5, f4| 90.49                 | 76.25               |
| f11, f9, f10, f5, f4, f2 | 91.25               | 77.32               |
| f11, f9, f10, f5, f4, f2, f3 | 91.74             | 80.36               |
| f11, f9, f10, f5, f4, f2, f3, f1 | 90.85           | 79.11               |
| f11, f9, f10, f5, f4, f2, f3, f1, f6 | 93.57             | 79.11               |
| f11, f9, f10, f5, f4, f2, f3, f1, f6, f8 | 93.44            | 81.79               |
| f11, f9, f10, f5, f4, f2, f3, f1, f6, f8, f12 | 93.57            | 80.71               |
| f11, f9, f10, f5, f4, f2, f3, f1, f6, f8, f12, f7 | 93.3             | 80.36               |

Table 4. Sensitivity and Specificity of system with combination feature input

| Feature     | Sensitivity (%) | Specificity (%) |
|-------------|-----------------|-----------------|
| f11         | 77.78           | 68.21           |
| f11, f9     | 78.41           | 73.55           |
| f11, f9, f10| 80.86           | 71.69           |
| f11, f9, f10, f5 | 82.94       | 73.31           |
| f11, f9, f10, f5, f4 | 80.05       | 70.34           |
| f11, f9, f10, f5, f4, f2 | 78.82       | 74.14           |
| f11, f9, f10, f5, f4, f2, f3 | 83.82       | 75.24           |
| f11, f9, f10, f5, f4, f2, f3, f1 | 83.79     | 72.91           |
| f11, f9, f10, f5, f4, f2, f3, f1, f6 | 83.93    | 71.78           |
| f11, f9, f10, f5, f4, f2, f3, f1, f6, f8 | 84.77    | 76.90           |
| f11, f9, f10, f5, f4, f2, f3, f1, f6, f8, f12 | 85.5     | 78.23           |
| f11, f9, f10, f5, f4, f2, f3, f1, f6, f8, f12, f7 | 83.26   | 75.40           |

Table 5. Accuracy of system with variation number of neurons

| Neuron number | Accuracy (%) | Sensitivity (%) | Specificity (%) |
|---------------|--------------|-----------------|-----------------|
| 70            | 82.5         | 89.26           | 67.07           |
| 80            | 80.71        | 85.33           | 74.21           |
| 90            | 79.64        | 86.49           | 69.46           |
| 100           | 79.28        | 82.32           | 73.22           |
| 110           | 80.18        | 84.71           | 73.22           |
| 120           | 81.43        | 83.65           | 77.14           |
| 130           | 80.71        | 82.09           | 78.23           |
| 140           | 81.61        | 82.75           | 80.05           |
| 150           | 81.96        | 84.16           | 78.93           |
| 160           | 80.71        | 80.89           | 79.93           |
| 170           | 80.54        | 81.94           | 79.24           |

Table 3 shows that there is a significant increase in accuracy of inputs RBFN with feature combinations compared to single feature inputs, a high difference is shown in accuracy when using only one feature input of 77.77%, while when using two features the accuracy increased by 11% to 88.04%. From the table also known that by the more combination of features used as input the better training accuracy obtained, because the table shows an increasing trend. The most optimal combination is obtained by 9 features of combination with training accuracy of 93.57%. The column of testing accuracy also indicating an increase trend to the more number of features. But The highest testing accuracy obtained by the combination of 10 features with 81.7%, 84.77 and 76.90% in terms of accuracy, sensitivity and specificity respectively.
From the most optimal combination, then the system tested by varying the number of neurons in RBFN classifier algorithm, the results showed in table 5. From the table its found that the most optimal number of neurons for the classification system that has been build is 150 neurons on the hidden layer with an accuracy of 81.6%.

4. Conclusion
In this study a drowsiness detection system has been developed using radial basis function network as classifier with electrocardiographic RR statistical feature. The system detect alert and drowsy subject from these ECG feature. The study conducted by varying the input feature to RBFN. From the system evaluation obtained that the best feature to detect drowsiness is maximal value of RR interval. A combination feature also conducted and the best performace is obtained from 10 combination features. While from varying the one of RBFN parameter method, the best number of neuron is 150 in the RBFN hidden layer.

5. Reference
[1] WHO 2015 Global Status Report On Road Safety 2015 WHO Library Cataloguing-in-Publication Data
[2] Lee B-L., Lee B-G., Chung W-Y 2016 Standalone Wearable Driver Drowsiness System in Smartwatch. IEEE Sensors Journal,16,13
[3] Padmanabhan S, 2015 Drowsiness Detection by HRV Analysis Thesis, Department of Electrical Engineering California State University
[4] Chui K, Tsang K, Chi H, Ling B, Wu C 2015 An Accurate ECG Based Transportation Safety Drowsiness Detection Scheme IEEE Transaction ON Industrial 1551-3203
[5] Piotrowski Z, Szy pulpka M, 2017 Classification of falling asleep states using HRV analysis Biocybernetics and biomedical engineering 37 290-301
[6] Gupta N, Najeeb D, Gabrielian V, Nahapetian A. 2015 Mobile ECG-Based Drowsiness Detection 14th IEEE Annual Consumer : Communication & Networking Conference 17 29-32
[7] Ghaderzadeh M, Fein R, Standring A, 2013 Comparing Performance of Different Neural Networks for Early Detection of Cancer from Benign Hyperplasia of Prostate Applied Medical Informatics 33 45-54
[8] Massoz Q, Langlois C, Verly J. G. 2016 The Ulg Multimodality Drowsiness Database (called DROZY) and Examples of Use IEEE
[9] Jovanović R. Ž, Sretenović A. A. 2017 Ensemble of Radial Basis Neural Networks With K-means Clustering for Heating Energy Consumption Prediction FME Transactions 45 51-57
[10] Sokolova, M., Lapalme, G. 2009. A systematic analysis of performance measures for classification tasks. Information Processing and Management 45 427–437