Development of Drowsy Driving Accident Prediction by Heart Rate Variability Analysis

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***Abstract*—Drowsy driving accidents can be prevented if it can be predicted in advance. The present work aims to develop a new method for predicting a drowsy driving accident based on the fact that the autonomic nervous function affects heart rate variability (HRV), which is the fluctuation of the RR interval (RRI) obtained from an electrocardiogram (ECG). The proposed method uses HRV features derived through HRV analysis as input variables of multivariate statistical process control (MSPC), which is a well-known anomaly detection method in process control. Driving simulator experiments demonstrated that driver drowsiness was successfully predicted seven out of eight cases before drowsy driving accidents occur.**

I. Introduction

According to the traffic accident statistics reported by Japanese National Police Agency, 17.6% of driving accidents in 2013 were caused by drowsy driving including falling asleep at the wheel. To prevent such accidents, an advanced driver-assistance system that can detect driver drowsiness or predict drowsy driving accidents and provides a warning would be effective.

Many drowsiness detection techniques have been proposed. One method is to use sheet pressure or pulse wave sensors for driver condition monitoring [1]. However, such sensors cannot always work due to changes in driving positions. Another method is to detect the vestibulo-ocular reflex (VOR) deterioration, which is a sign of drowsiness [2]. Nevertheless, VOR monitoring is difficult in dark environments because it is based on image analysis.

Heart rate variability (HRV), which is the RR interval (RRI) fluctuation of an electrocardiogram (ECG), is a well-known phenomenon reflecting the autonomic nervous function; thus driver drowsiness may be detected through analyzing HRV. Actually, many driver drowsiness detection methods based on HRV analysis have been proposed. For example, Yanagidaira et al. proposed a method based on heart rate and HRV frequency analysis [3]. However, its detection rate was 55%, and there is room for further improvement. The objective of the present work is to develop a new method for predicting drowsy driving accidents based on HRV analysis. The proposed method consists of two parts: HRV feature extraction from RRI data of a driver, and drowsy driving accident prediction by applying an anomaly detection framework to the extracted HRV features. Multivariate statistical process control (MSPC), which is a well-known anomaly detection method in process control, is used for prediction. Driving simulator experiments were performed to verify the proposed method.

II. Heart Rate Variability Analysis

HRV reflects autonomic nervous activity, therefore HRV analysis has been used for stress or drowsiness detection as well as cardiovascular disease monitoring [4], [5], [6]. This section explains the HRV features used for drowsiness detection.

A. RR Interval

A typical ECG trace (standard lead II) of a cardiac cycle consists of some peaks as shown in Fig 1, and the highest peak is called the R wave. The RR interval (RRI) [ms] is defined as the interval between an R wave and the next R wave. A part of raw RRI data collected from a healthy person is shown in Fig. 2 (a). Since the raw RRI data are not sampled at equal intervals, the data are interpolated by using spline and resampled at equal intervals for analysis. Figure 2 (b) shows the resampled RRI data whose sampling interval is one second.

B. Time Domain Features

The following time domain features are calculated from raw RRI data [5].

- **meanNN**: Mean of RRI.
- **SDNN**: Standard deviation of RRI.
- **RMSSD**: The root mean square of difference of adjacent RRI.
- **Total power**: Variance of RRI.
- **NN50**: The number of pairs of adjacent RRI whose difference is more than 50 milliseconds.

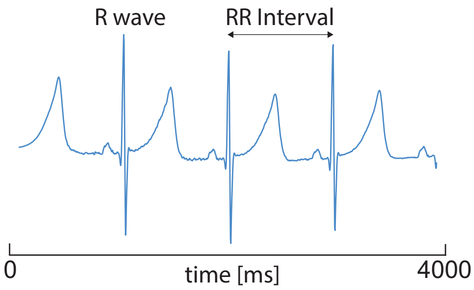

Fig. 1. An example of a typical ECG trace

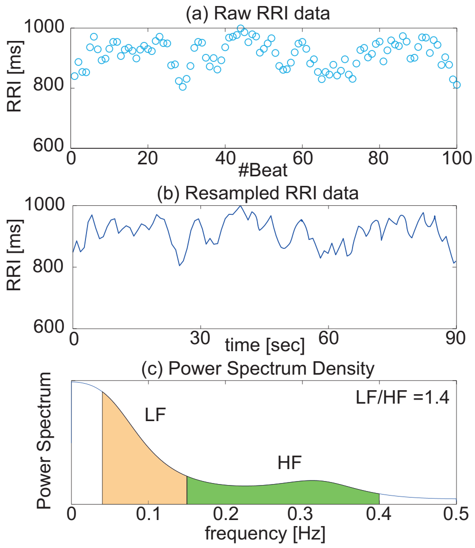

Fig. 2. An example of HRV analysis: (a) raw RRI data, (b) resampled RRI data and (c) the PSD and its LF/HF

C. Frequency Domain Features

The following frequency domain features are obtained through a power spectrum density (PSD) of the resampled RRI data, and the PSD can be calculated by using an autoregressive (AR) model [5].

- **LF**: The power in low frequency range (0.04Hz - 0.15Hz) in a PSD. LF reflects sympathetic nervous system activity and parasympathetic nervous system activity.
- **HF**: The power in high frequency range (0.15Hz - 0.4Hz) in a PSD. HF reflects parasympathetic nervous system activity.
- **LF/HF**: Ratio of LF to HF. LF/HF expresses the balance between the sympathetic and the parasympathetic nervous system activity.

Figure 2 (c) shows the PSD and its LF/HF of the resampled RRI data shown in Fig. 2 (b). According to HRV analysis guideline, RRI data should be measured for at least three minutes to conduct precise frequency analysis [5].

III. Drowsy Driving Accident Prediciton

In this section, the description will be made on MSPC and the procedure of HRV-based drowsy driving accident prediction.

A. Multivariate Statistical Process Control (MSPC)

MSPC is an useful technique for monitoring multivariate processes and has been widely used in many processes [7], [8]. MSPC can detect faults that cannot be detected by monitoring each variable independently, because it models the correlation among variables with principal component analysis (PCA) and defines the normal operating condition (NOC) with two monitored indexes, i.e., the T^2 and Q statistics [9].

It is assumed that a data matrix is given by $\boldsymbol{X} \in \Re^{N\times M}$ whose ith row is the ith sample $\boldsymbol{x}_i \in \Re^M$.

The singular value decomposition of $\boldsymbol{X}$ is described as

$$\begin{aligned} \boldsymbol{X} &= \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^T \\ &= \begin{bmatrix} \boldsymbol{U}_R & \boldsymbol{U}_0 \end{bmatrix} \begin{bmatrix} \boldsymbol{\Sigma}_R & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{\Sigma}_0 \end{bmatrix} \begin{bmatrix} \boldsymbol{V}_R & \boldsymbol{V}_0 \end{bmatrix} \end{aligned} \tag{1}$$

where $\boldsymbol{U}$ is the left singular matrix, $\boldsymbol{\Sigma}$ is the matrix whose diagonal elements are singular values and $\boldsymbol{V}$ is the right singular matrix. In PCA, the loading matrix $\boldsymbol{V}_R \in \Re^{M\times R}$ is derived as the right singular matrix of $\boldsymbol{X}$ and the column space of $\boldsymbol{V}_R$ is the subspace spanned by principal components. Here, $R\,(\leq M)$ denotes the number of principal components retained in the PCA model. All variables are mean-centered and appropriately scaled. The score matrix $\boldsymbol{T}_R \in \Re^{N\times R}$, which is a projection of $\boldsymbol{X}$ onto the subspace spanned by principal components, is given by

$$\boldsymbol{T}_R = \boldsymbol{X}\boldsymbol{V}_R. \tag{2}$$

$\boldsymbol{X}$ can be reconstructed or estimated from $\boldsymbol{T}_R$ with linear transformation $\boldsymbol{V}_R$.

$$\hat{\boldsymbol{X}} = \boldsymbol{T}_R\boldsymbol{V}_R^{\mathrm{T}} = \boldsymbol{X}\boldsymbol{V}_R\boldsymbol{V}_R^{\mathrm{T}} \tag{3}$$

The information lost by the dimensional compression, that is, errors, is written as

$$\boldsymbol{E} = \boldsymbol{X} - \hat{\boldsymbol{X}} = \boldsymbol{X}(\boldsymbol{I} - \boldsymbol{V}_R\boldsymbol{V}_R^{\mathrm{T}}). \tag{4}$$

Using the errors, the Q statistic is defined as

$$\begin{aligned} Q &= \sum_{m=1}^{M}(x_m - \hat{x}_m)^2 \\ &= \boldsymbol{x}^T(\boldsymbol{I} - \boldsymbol{V}_R\boldsymbol{V}_R^T)\boldsymbol{x} \end{aligned} \tag{5}$$

where $\boldsymbol{x}$ is a newly measured sample. The Q statistic is the squared distance between the sample and the subspace spanned by principal components. In other words, the Q statistic is a measure of dissimilarity between the sample and the modeling data from the viewpoint of the correlation among variables.

In addition, to monitor anomaly on the subspace spanned by principal components, Hotelling's T^2 statistic is used.

$$\begin{aligned} T^2 &= \sum_{r=1}^{R}\frac{t_r^2}{\sigma_{t_r}^2} \\ &= \boldsymbol{x}_i^T\boldsymbol{V}_R\boldsymbol{\Sigma}_R^{-2}\boldsymbol{V}_R^T\boldsymbol{x}_i \end{aligned} \tag{6}$$

where σ_{t_r} denotes the standard deviation of the rth score t_r. The T^2 statistic expresses the Mahalanobis distance from the origin in the subspace spanned by principal components. When the T^2 statistic is small, the sample is close to the mean of the modeling data. An anomaly is detected when either the T^2 or Q statistic exceeds the corresponding control limit. An advantage of MSPC is that a drowsiness detection model can be constructed by using only normal (awakening) data.

B. *Drowsy Driving Accident Prediction Procedure*

In the proposed method, drowsy driving is predicted by the following procedure through integrating MSPC and HRV analysis. In addition, this procedure is performed per participant.

1) Measure RRI from a driver.
2) Extract HRV features from the measured RRI.
3) Normalize the extracted HRV features with the mean and the variance.
4) Calculate the T^2 and Q statistics from the normalized HRV features by using Eqs. (5) and (6).
5) Judge that a drowsy driving accident will occur in the near feature when either statistic is outside its control limit.
6) Return to step 1).

In the proposed method, the number of principal components and the control limits are tuning parameters.

IV. Experiment

RRI data and drowsiness level data were collected through experiments using a driving simulator. In this work, a drowsy driving accident prediction model was constructed for each driver to cope with the driver individuality.

A. *Data Acquisition*

The RRI data and the face image data of experimental participants (drivers) were collected while driving of a virtual vehicle on the simulator. Experimental participants drove on a night loop course for two hours so that they got drowsy. During experiments, the RRI data were measured by using an RRI telemetry device [10] and sent to a PC by wireless. In addition, the face image data were captured by an USB webcam. The total number of experimental participants was 27. The experimental participants consist of seventeen males in twenties, eight females in twenties, one female in thirties, and one female in forties. The Research Ethics Committee of Shizuoka University approved this experiment and individual participant consent was obtained.

The drowsiness level was derived from the captured face image by using an expressional drowsiness estimation method [11]. First, face images of the experimental participants were clipped every twenty seconds from the face image data. Following an awaking level criterion shown in Fig. 3, three trained referees evaluated the drowsiness level independently from the face images sorted in a random order. Next, the twenty-second evaluation values were given by averaging evaluations of each referee. Then, by averaging the consecutive three twenty-second evaluation values, the final one-minute evaluation values were obtained.

Finally, the RRI data measured from experimental participants were labeled as the awakening RRI data or the drowsy RRI data according to the evaluated drowsiness level. In this work, the awakening condition was defined that the drowsiness level is less than 2.0.

Two types of datasets, labeled as an accident RRI dataset or an awakening RRI dataset were constructed. In this experiment, the number of accident RRI dataset was eight because

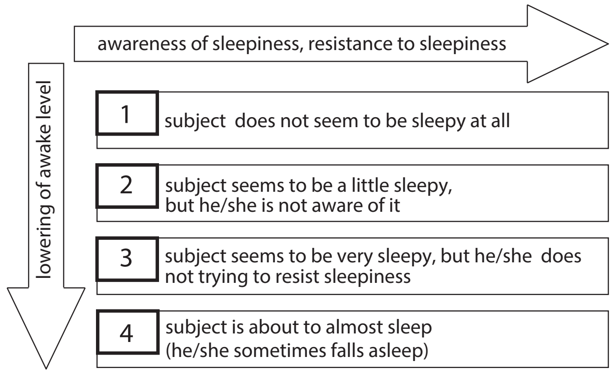

Fig. 3. An awaking level criterion [11]

eight participants had caused drowsy driving accidents. The RRI data of 20 minutes, from 15 minutes before to five minutes after an accident, were clipped as an accident RRI dataset. On the other hand, awakening RRI datasets, which were not used for modeling, consisted of RRI data of 20 minutes recorded in the awakening.

B. *HRV Features*

A rectangular sliding window was applied to RRI datasets, and eight HRV features described in Sec. II were calculated within each window. The window size was three min. An AR model was used to calculate frequency domain features, and its order was ten. The HRV features extracted from an awakening RRI dataset and an accident RRI dataset of Participant No. 7 are shown in Figs. 4 and 5. Red vertical lines in Fig. 5 indicate the time the accident occured. These figures show that some HRV features such as SDNN, Total Power, NN50, LF and LF/HF in the accident case, are approximately larger than the awakening case; thus the drowsiness is related to the autonomic nervous function. However, it is difficult to detect drowsiness by monitoring respective HRV features because some features, such as LF and LF/HF in the awakening case are partially larger than the accident case. Hence multiple HRV features should be monitored together.

C. *Model Construction*

The HRV features extracted from the awakening RRI data of each experimental participant were used for the model construction, and their length was 250 beats (about three minutes). Only one principal component was adopted in MSPC and the control limits of the T^2 and Q statistics were determined so that they represented 80% confidence limits. In other words, the control limits were set so that 80% of samples representing the awakening condition were below the control limits and the other 20% were outside. They were determined by trial and error.

D. *Model Verification*

The prosed HRV-based drowsy driving prediction method was verified through its application to experimental datasets. The purpose of this verification is to test whether or not

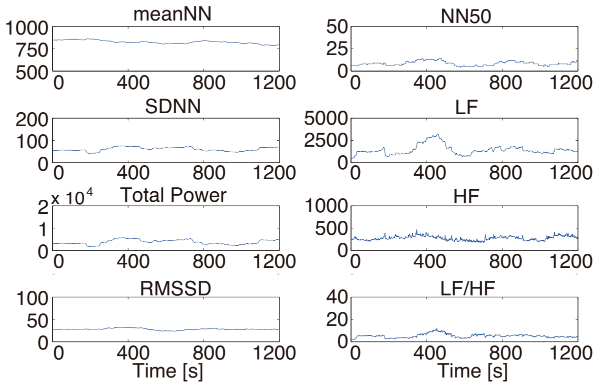

Fig. 4. HRV features (awakening dataset, Participant No. 7)

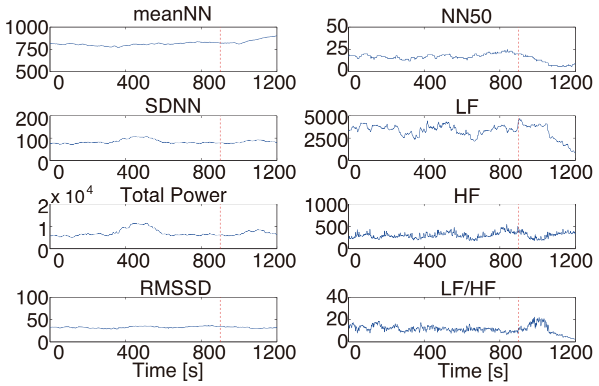

Fig. 5. HRV features (accident dataset, Participant No. 7)

driver drowsiness can be detected prior to an accident by the proposed method.

Although all eight datasets were tested, only one result of Participant No. 7 is shown in Figs. 6 and 7. Figure 6 shows the drowsiness detection result of the awakening data and Fig. 7 shows the result of the accident data. In these figures, the horizontal dashed lines express the control limits of the T^2 and Q statistics.

The T^2 statistic of the accident dataset exceeded its control limit continuously before the accident, while that of the awakening dataset rarely exceeded. However, the Q statistic of the awakening dataset also partially exceeded its control limit. This indicates that the Q statistic reacted to HRV features changes caused by other than drowsiness. Other datasets showed similar tendency except Participant No. 6. In this case, the T^2 statistic was large even in the awakening condition. According to the evaluated drowsiness level of Participant No. 6, he/she had been drowsy from the beginning of the experiment, and it was difficult to discriminate the awakening condition and the drowsy condition. The proposed method predicted seven out of eight accident cases before the accident.

These results indicate that the proposed method can predict drowsy driving accidents in advance.

V. CONCLUSIONS

A new method for predicting drowsy driving accident was proposed by integrating HRV analysis and MSPC. The possibility of realizing an HRV-based drowsy driving accident prediction system was demonstrated through the driving simulator experiments. In the future work, the proposed method will be realized as a smartphone application.

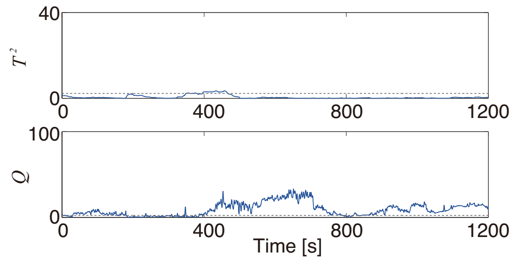

Fig. 6. Drowsiness detection results (awakening dataset, Participant No. 7)

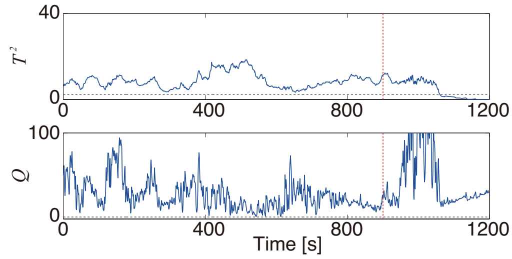

Fig. 7. Drowsiness detection results (accident dataset, Participant No. 7)

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