Identification of Stress State for Drivers Under Different GPS Navigation Modes

JINGBIN LI1, JIAHUI LV1, BEOM-SEOK OH2, (Member, IEEE), ZHIPING LIN3, (Senior Member, IEEE), AND YA JUN YU1,4, (Senior Member, IEEE)

1Department of Electrical and Electronic Engineering, Southern University of Science and Technology, Shenzhen 518055, China
2Department of Computer Science, Gyeongsang National University, Jinju 52828, South Korea
3School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798
4University Key Laboratory of Advanced Wireless Communications of Guangdong Province, Southern University of Science and Technology, Shenzhen 518055, China

Corresponding author: Ya Jun Yu (yuyj@sustech.edu.cn)

This work was supported in part by the Fundamental Research Project (free exploration) funded by the Science and Technology Innovation Committee Foundation of Shenzhen, China, under Grant JCYJ20170817104824042.

ABSTRACT

It is commonly known that Global Positioning System (GPS) can alleviate travelling difficulties of automobile drivers, and generally we hold the view that it reduces the driver’s stress when they are in unfamiliar road conditions. In this research, an in-laboratory experiment and an in-car experiment are conducted to find out whether GPS instructions can reduce or may induce additional mental stress of drivers. Electrocardiography (ECG) signals are collected in the experiments and the extracted heart rate variability (HRV) features are used for analysis. Three binary classifiers, specifically Support Vector Machine, $k$-Nearest Neighbor ($k$-NN) and Random Forest, are trained based on the data collected in the in-laboratory experiment, where the stress state is elicited by the Stroop color word Test. The $k$-NN classifier outperforms the other two classifiers, and thus is applied to the data collected in the in-car experiment, to identify drivers’ stress state under different driving events, such as waiting for traffic lights, turning, under GPS instructions, and traffic conditions like overtaking, or changing lanes. During each event, whether the driver is in stress or relaxed state for each time instant is predicted based on the trained classifier. The percentages of time that the driver is in stress state for each type of events are computed. It shows that GPS instructions cause the second largest time-percentage of stress state, lower than that caused by the turning event, but higher than that caused by the events of waiting for traffic lights and other traffic conditions.

INDEX TERMS

Driver stress, GPS navigation, $k$-NN classifier, Stroop color word test, HRV features, ECG signal.

I. INTRODUCTION

In-car driving navigation making use of Global Positioning System (GPS) has become a standard operation for drivers, except to commute between workplace and home, or on other familiar routes. Driving navigation significantly mitigates driver’s anxieties induced due to not knowing or not familiar with routes. Travelling to new places by self-driving becomes an unprecedentedly pleasant experience thanks to the technology development.

While navigation instructions become more and more accurate, clear, and in real-time, the incessant grinding-out of instructions such as keeping right, turning left, somewhat is annoying, or inducing additional mental stresses. It has shown that high stress level of drivers is one of the leading causes of car accidents, along with fatigue, intoxication, and aggressive driving [1], because high mental stress may affect driver’s judgement and reaction under critical situation. Therefore, to provide drivers with feedbacks in forms of cautions, warnings or suggestions, driver stress monitoring has always been an important constituent of an intelligent vehicle system since the concept initially appeared [2], [3] in 1990s.

A large variety of signals have been used to recognize stress states, such as facial expressions, gestures, or physiological signals like Electrocardiography (ECG), Electroencephalo-graphy (EEG), Galvanic Skin Response (GSR), Electro-myogram (EMG), Blood Volume Pressure (BVP), and Respiration Rate [4]. Among these signals,
EEG and ECG are the most widely used signals in stress level detection and monitoring because of the rich features extractable from the signals.

Many researches make use of EEG [5]–[7] and ECG [8]–[10], [30] signals to design stress classifiers to monitor or analyze stresses. The general strategy is to use a stressor – the technical term of the stress inducing factor – to evolve stresses of testers, collect EEG or ECG signals, extract related features from the signals, and finally train and verify classifiers using machine learning methods. The commonly used stressors include Stroop color word test (SCWT) [6], [8], undertaking real work with different levels of stress [5], performing arithmetic calculation [7], [10], N-back task [30], and watching videos [5], [9]. In training and testing of classifiers, statistical machine learning methods such as Support Vector Machine (SVM) [6], [7], [9] and k-Nearest Neighbor (k-NN) [8], [9] are more often used than neural networks [10]. Decision fusion [7] achieved by fusing outputs from multiple classifiers is also reported, whereas online multiple-task learning algorithms [5] are proposed for real-time processing.

While both EEG and ECG signals become more and more easy to obtain, the ECG signal has the advantage that the measurements of cardiac activity are robust and affordable. More importantly, a wealth of information, for example, Heart Rate Variability (HRV) features [11], can be extracted from ECG. A recent study further confirmed that ECG signals are ranked as the optimal bio-signal for accessing driving stress [12].

Many wearable devices like smartwatch can efficiently acquire ECG and HRV signals. Compared to ECG signals, HRV features are even easier to obtain since not full ECG signals with detailed QRS complex are required to extract HRVs; instead, simple version of ECG containing only the peak information of R waves is sufficient for this purpose. Hence, many simple wristbands, which are much cheaper than smartwatches and thus affordable to many people, can be used for HRV detection. In driving scenario, ECG and HRV detections have the additional advantages that driver’s sights are not blocked, and body movements are not restricted by attached sensors and wires, such that drivers can control the car freely.

Thus, in this research, the ECG signal and its extracted HRV features are used to study the stress state of drivers under different driving modes. Many stressors, such as different driving situations (rest, on highway, or in city) and speeds [13], different driving events (overtaking, hand braking, or crossroad) [14], [15], or transiting road tunnel [16], have been studied. Research in [17] also uses data collected both from real-world driving and simulator driving tasks to train neural network for personalized stress recognition. A recent study [12] further confirmed that a significant correlation exists between the driving stress marker and ECG.

A preliminary study to investigate driver’s mental stress with GPS navigation in use by measuring and analyzing ECG signal and its deduced HRV features has been published in [18].

However, in most of these studies, the stress states of the drivers are obtained through questionnaire / self-assessment [4], [12], [16], video [13], stress rating based on task conditions [13], [14], [17], or determined by the statistical significance of the difference between the interested condition and the relaxed condition [18]. In these researches, especially in the investigation of drivers’ stress when GPS navigation is in use, no ground truth was based.

To facilitate our investigation on the identification of stress state for drivers under different GPS navigation modes in this research, we conducted an in-laboratory experiment to provide a ground truth of stress state for an in-car experiment. The justification of the link between the in-laboratory experiment and the in-car experiment will be given in Section II.

The rest of the paper is organized as follows: In Section II, the methodology of this study is proposed. The rationality of the methodology is justified. Section III describes the in-laboratory experiment, including the objective, subjects, setup and procedures. Section IV introduces the HRV features used in the stress state and relaxed state classification. The classifier trained by the in-laboratory data is illustrated in Section V. In Section VI, the in-car experiment is described in detail. The processing of the collected ECG data and identification of stress state for drivers under different navigation modes are presented in Section VII. The paper is concluded in Section VIII.

II. METHODOLOGY AND JUSTIFICATION
The objective of this research is to investigate if in-car GPS navigation can reduce or may induce additional stress to drivers. The signals used for this investigation are ECG data, or more specifically, the HRV features extracted from the ECG data.

A. METHODOLOGY
As stated in Section I, the SCWT has been used as a stressor in many research work [6], [8]. In this study, an in-laboratory experiment based on the SCWT was developed to establish the ground truth of stress condition. A classifier is then trained based on the data collected in the in-laboratory experiment. The ECG signals of drivers collected in an in-car laboratory are predicted using the trained classifier to identify the stress state under different driving conditions, including the use of in-car navigation system.

In this methodology, the SCWT selected as the stressor in the in-laboratory experiment is to create a situation similar as that of real driving. To justify this, it is necessary to understand what stress is and what the types of stresses are.

B. STRESSES INDUCED BY SCWT VS. BY DRIVING
It is known that stresses are induced due to increased command upon human machinery; it may be seen as a relationship between people and the environment which demands more resources than that people have or endanger people’s well-being [19]. Under stresses produced by various factors, human responds in general in a stereotyped manner for the
objective to maintain homeostasis [20], i.e., the physiological response of human to different stressors fundamentally are similar. Even though, the effects of environmental factors to humans may be on physical or on mental well-being [21].

In this point of view, stressors are classified to physical stressor and mental stressor [22]. In driving stress related research [22], physical stresses are elicited by driving in cold or hot environment, while mental stresses are elicited by calculating simple arithmetic operation during driving, driving in a noisy environment or in a dark alley. In view of this, the stress that may be induced in this research by different GPS navigation modes or any events during the normal driving, such as turning, waiting, overtaking, all belongs to mental stress.

There are many classical in-laboratory stress protocols which have been proved to be effective in eliciting stress, and thus enabling the investigation of stress under controlled conditions [23]. Such stress protocols include Cold Pressor Test (CPT) [24], Trier Social Stress Test (TSST) [25], the SCWT [26], [27], N-back task [30], etc. The CPT is a test in which the participants are required to place their non-dominant hand in a box filled with ice-cold water for as long as possible. The CPT test is thought to elicit pain and physiological responses and is considered as a physical stressor. The TSST includes a mock job interview where the participant needs to give a free speech in front of an evaluating audience and a video camera; the participant meanwhile needs to solve a serial subtraction task to elicit higher level stresses. The SCWT is a cognitive task which requires the participants to name the printed colors of items shown on several cards [26], [27]. The incongruent color-word may result in a conflict between dominant (read the word) and non-dominant (name the color of the word) reactions and thus induce stress.

Both stresses elicited by TSST and SCWT are mental stress, but the TSST may somehow rely on the corporation of audiences. Thus, the SCWT is a good choice of stressors to induce mental stress.

Due to the stereotyped response of human beings to different types of stresses, and more importantly, due to the same attributes of the stresses induced by driving factors that we considered and that induced by the SCWT, we feel that it is justifiable to use the classifier trained by the data from the SCTW to predict the stress state during driving.

C. CONTROLLED VS. NATURAL ENVIRONMENT EXPERIMENTS

Besides the relevance between the two experiments, the in-laboratory experiment is conducted under a controlled condition, whereas the in-car experiment is conducted in a natural environment. In controlled condition, the testers mostly keep still, while in natural environment, there are confounding influence of motion. Such differences may impact on two aspects.

First, the ECG signal collected in natural environment may contain motion artifacts, including the body motions and car vibrations; and second, the driver’s muscle actions may contribute to the stress level, reflected in ECG signal.

For the first point of motion artifacts, the in-car experiment has minimized the body motion impact, for the driving activity constrains the motions of the testers only to braking, steering wheels, and slight turning of body above chest. Moreover, the artifacts have more impact on the ECG waveforms than on the R-peak detections. Mature detection algorithms [28], [29], by involving filtering and correlation techniques, are sufficiently robust in most cases to suppress noises and resist against artifacts caused by limited motions, especially when only R-peaks have to be detected. The research in [29] showed that both the precision and sensitivity of R-peak detection of ECG signal obtained during driving are higher than 99.2%.

Besides the body motion, car vibrates during driving. The vibration frequency of car in general is random, depending on many factors acting together. However, the phenomenon is dominated by the suspension natural frequency, which is in the range of 1-2 Hz [32]. This frequency range is not overlapping with the spectrum peak power of the QRS complex, typically ranging from 4-12 Hz [33].

For the second point of the impact of stresses induced by muscle activity on the changes of ECG signals, the research in [34] specially designed two tests to study the effects. Both tests showed that in driving tasks, the muscle activities have little effect on the stress activity detection.

Based on the above analysis and observations, we feel that the HRV features obtained from the natural environment driving experiment should be quite similar as that obtained from the controlled environment, e.g., the SCWT experiment.

III. IN-LABORATORY EXPERIMENT

To understand the relation between the HRV features and mental stress, an in-laboratory experiment is designed to collect testers’ ECG signal under both relaxed and stress states. HRV features of the ECG signals are extracted. Eighty percent of the data are used to train binary classifiers to classify the relaxed state and stress state, and the remaining 20% data are used for verification.

In this section, the details of the in-laboratory experiments are described. An overview of the experiment is followed by the descriptions of experiment subjects, equipment, and procedures.

A. EXPERIMENT OVERVIEW

In this experiment, ECG data of volunteers are collected under both relaxed state and stress state.

The stress of testers is induced by the SCWT. The SCWT consists of colors that are written in words but in the wrong color ink. The tester needs to state the color that the word is written in and ignore whatever the actual word is. For example, if you see the word “blue” but it’s written in red ink, the correct answer would be “red”. This game can date back to the 1930s that measures cognitive functioning. When taking the test, the testers are stressful because they must do...
their best to eliminate the interference from the words and answer as quickly as possible the correct color ink in a limited time duration. SCWT is therefore conventionally used as an effective stress elicitation [26].

During the test, ECG signals and video signals recording the facial expression of the subjects are collected. Four devices, i.e., two computers, an ECG monitor and a video camera, are used. Each test takes about 15 minutes.

B. SUBJECTS AND QUESTIONNAIRES
The study group consists of 19 volunteers (referred to as subjects in the study) between 18-24 years old. The numbers of male and female subjects are 12 and 7, respectively. Each subject was informed in detail about the study, and consents to having video and ECG signal recorded during the test were obtained prior to data collection.

A self-assessment questionnaire was conducted after the experiment. Subjects were asked to answer his/her subjective stress level during the test. The scale of the subjective stress measurement was indicated to be 10 for the highest stress and 1 for the lowest. Note that the self-assessment questionnaire was not used as a ground truth of stress state. It provides only additional information to exclude some extreme cases, as to be stated in the first paragraph of Section V.

C. EQUIPMENT AND SETUP
In this experiment, subjects take the SCWT on a desktop computer installed with the developed test. Meanwhile, ECG signals are acquired by a GE B30 monitor with three electrodes placed on the chest of the subject, as shown in the middle part of Fig. 1, where RA, LA and LL refer to right arm, left arm and left leg, respectively. The collected ECG data, through a cable, are transmitted to another computer for real time display and further processing. The overall system is shown in Fig. 1, where the left column is the screen shots of the desktop when the subjects are under the relaxed condition or engaged in the test.

D. PROCEDURES
The test goes through 3 functioning stages in the order of a preparation stage (30 seconds), a relaxed stage (150 seconds), and a stress stage (180 to 240 seconds). A 30-second break stage is inserted between every two adjacent functioning stages, allowing subjects to adjust and prepare for the coming stage. The procedure and durations of each stages are shown in Fig. 2. The main actions to be taken in each functioning stage are described as follows:

**Preparation stage:** Instructions are given during this stage prior to the formal test. The entire procedure of the test including the SCWT and relaxed stages is explained to the subject. The subject is asked to calm down and to get familiar with the user interface (UI).

Shown in Fig. 3, the UI in this stage contains a header on the top, a standard color bar on the left, and an information region on the right, surrounding the center blank region. The header shows the instruction to the subject. The standard color bar shows the 7 colors that will be used in the SCWT, and the information region shows the basic information about the test, such as the current test stage, the right answer number over the total test times, etc.

When the subject is ready, the computer program that will automatically go through the different stages is launched and meanwhile the ECG data acquisition system [9] is simultaneously started.

**Relaxed stage:** In this stage, the subject is relaxed by listening to a piece of music for 150-second duration. The music is slow and soft. The user interface (UI) in this stage is similar as that in preparation stage, except that a music icon is shown in the center, as shown in the top-left corner in Fig. 1.

**Stress stage:** In this stage, the subject takes the SCWT with increasing difficulty levels. The user interface (UI) of the
The most significant features in the time domains are the mean value of heart rate (mHR), the mean (ANN) and standard deviation (SDNN) of RR intervals, the number of RR interval that differ larger than 20ms (NN20) or 50ms (NN50) than its previous RR interval, the percentage of NN20 (PNN20) and NN50 (PNN50), the RMS difference between adjacent RR intervals (RMSSD) and the high order cumulant (cmmn) [8] calculated by $1/n \sum_{i=1}^{n} (NN_i - ANN)^a$, where $NN_i$ is the $i$-th RR interval and $a = 2, 3, 4$ is the order number.

**B. FREQUENCY DOMAIN FEATURES**

Frequency domain analysis is based on the power spectral density of RR-interval signal [36]. The features include total spectral power in low frequency domain (0.04-0.15 Hz), denoted as LF, in high frequency domain (0.15-0.5 Hz), denoted as HF, normalized low frequency (nLF) or high frequency (nHF) spectral power, difference between nLF and nHF, denoted as nLFHF, and the ratio of low frequency to high frequency spectral power denoted as LF/HF [35].

**C. NONLINEAR FEATURES**

Nonlinear features are extracted from the Poincare plot which is a graph of $NN_i$ on the x-axis versus $NN_{i+1}$ on the y axis [37], where $NN_i$ is the $i$-th RR interval. Several features are calculated based on the Poincare plot, including the standard deviation across the line of identity ($y = x$), denoted as $SD1$, the standard deviation along the line of identity, denoted as $SD2$, $C_{UP}$ defined as $SD1_{up}/SD1^2$, $C_{down}$ defined as $SD1^2_{down}/SD1^2$, and the autocorrelation coefficients of the RR intervals, denoted as $CorrCoef$. Among these features, $C_{UP}$ and $C_{down}$ denote the relative contribution of $SD1_{up}$ or $SD1^2_{down}$ to $SD1^2$, where $SD1_{up}$ and $SD1_{down}$ are the standard deviations of the points above or below the line of identity.

**V. CLASSIFIER TRAINING AND EVALUATION**

The data collected in Session III are reviewed before they are used in the classifier training. If the after-experiment self-evaluation of stress from the tester is too low, and meanwhile the correct answer rate of the stress stage is larger than 60/65, the subject is considered not in stress state, and the data are excluded from the training. Based on these criteria, the data of 13 subjects are selected for the classifier training, including 10 male and 3 female volunteers aging from 18 to 24 years old.

**A. PERFORMANCE PARAMETERS**

Three binary classifiers are used to recognize the stress state, i.e., SVM, $k$-NN and Random Forest (RF). In this paper, classifiers are implemented in Python based on Scikit-learn library [38], which includes a wide range of state-of-the-art machine learning algorithms. For SVM classifier, the radial basis function kernel is chosen with penalty parameter $C = 10$, radial basis function (RBF) kernel with $\gamma = 0.01$. Five-fold cross-validation [39] is used to calculate the performance parameters of precision, sensitivity, specificity, and

![FIGURE 4. The user interface of the stress stage in the in-laboratory experiment.](image)
accuracy, which are formulated by

\[
\text{Precision} = \frac{TP}{TP + FP} \times 100\%,
\]
\[
\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\%,
\]
\[
\text{Specificity} = \frac{TN}{TN + FP} \times 100\%,
\]
and
\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%,
\]

where \(TP\) stands for True Positive, denoting the number of the samples in the stress state and recognized as stress state, \(TN\) stands for True Negative, denoting the number of the samples in the relaxed state and recognized as relaxed state, \(FP\) stands for False Positive, denoting the number of the samples in the relaxed state but recognized as stress state, and \(FN\) stands for False Negative, denoting the number of the samples in the stress state but recognized as relaxed state.

In these 4 performance parameters, Precision denotes the ratio of the samples which are really in the stress state to all the samples recognized as stress state; the sensitivity denotes the ratio of the samples which are recognized as the stress state to all the samples in stress state; specificity denotes the ratio of the samples recognized as in relaxed state to all the samples actually in the relaxed state; and accuracy denotes the ratio of the right classified sample, including stress state and relax state, among all the samples.

### B. DETERMINATION OF CLASSIFIER PARAMETERS

As mentioned in Section V-A, 5-fold cross-validation is used in the classifier training and testing. In 5-fold cross-validation, data are separate into 5 portions. Four portions are used to train the classifiers and the remaining portion is used to test (or validate) the performance. Such training and testing are iterated 5 times, each time a different portion of data being used for the test. The 5-iteration averages of the 4 performance parameters are calculated, respectively.

In 5-fold cross-validation for ECG signals, data from subjects may either be mixed first and then separated to 5 portions [17] or be separated according to subjects to 5 portions [31]. In the former case, although the data used for training are different from those for testing, they may be from the same subjects. The latter case guarantees that the data from the same subjects will not appear in both training set and testing set, suggesting better generalization of the trained classifiers when the tested performances are at similar level. In our study, separation of the data according to subjects is used. More specifically, in each iteration of training and testing, the data from 2 or 3 subjects are purely used for testing and no data of these 2 or 3 subjects are used for training in the same iteration.

Different parameters of the classifiers influence the performance of the classifier. For \(k\)-NN classifier, several \(k\) values, which denotes the number of the nearest neighbor samples used for classification, set from 1 to 20 with step-size of 2, were tested. The performance results are shown Fig. 5. From Fig. 5, we can see that the average values of the performance parameters reach the largest at \(k = 3\), but the differences from the cases with other values are insignificant. Considering the increasing computational load with the increase of \(k\), \(k = 1\) is used in this study.

For SVM classifier, several \(C\) values, specifically 0.1, 1, 10, 100, and 1000, and several \(\gamma\) values in the RBF kernel, specifically 0.01, 0.001 and 0.0001, were tested. The results are shown in Table 1. From Table 1, we can see that all the four performance parameters increase with increasing values of \(C\) and \(\gamma\). The best results are shown in bold style in Table 1. However, larger values of \(C\) and \(\gamma\) may cause overfitting of the trained classifier [40]. Table 2 shows the case that both \(C\) and \(\gamma\) take the largest values of 1000 and 0.01, respectively. It can be seen that the performance parameters fluctuate significantly among the five-fold scheme, indicating that the generalization ability is poor. Thus, to tradeoff between the
TABLE 2. The precision, sensitivity, specificity, and accuracy for $C = 1000$ and $\gamma = 0.01$ for the verification of SVM.

| No. of Fold | Precision | Sensitivity | Specificity | Accuracy |
|-------------|-----------|-------------|-------------|----------|
| 1           | 0.955     | 0.9827      | 0.9866      | 0.9732   |
| 2           | 0.9387    | 0.9082      | 0.9063      | 0.8578   |
| 3           | 0.9953    | 0.9895      | 0.9908      | 0.9841   |
| 4           | 0.9900    | 0.9948      | 0.9909      | 0.9922   |
| 5           | 0.8101    | 0.8466      | 0.7938      | 0.7680   |
| **Average** | 0.9459    | 0.9444      | 0.9151      | 0.9337   |

TABLE 3. Performances of SVM, $k$-NN, and RF when different combinations of HRV features are used for training.

| Classifier | Precision | Sensitivity | Specificity | Accuracy |
|------------|-----------|-------------|-------------|----------|
| SVM        | 0.7539    | 0.8911      | 0.8612      | 0.7967   |
| $k$-NN    | 0.9672    | 0.9696      | 0.9539      | 0.9619   |
| RF         | 0.9689    | 0.9595      | 0.9379      | 0.9566   |

| Classifier | Precision | Sensitivity | Specificity | Accuracy |
|------------|-----------|-------------|-------------|----------|
| SVM        | 0.8785    | 0.7845      | 0.6595      | 0.7908   |
| $k$-NN    | 0.8511    | 0.8576      | 0.7878      | 0.8258   |
| RF         | 0.8717    | 0.8683      | 0.8015      | 0.8436   |

| Classifier | Precision | Sensitivity | Specificity | Accuracy |
|------------|-----------|-------------|-------------|----------|
| SVM        | 0.6998    | 0.8623      | 0.8325      | 0.7529   |
| $k$-NN    | 0.9430    | 0.9461      | 0.9195      | 0.9336   |
| RF         | 0.9400    | 0.9370      | 0.9054      | 0.9262   |

| Classifier | Precision | Sensitivity | Specificity | Accuracy |
|------------|-----------|-------------|-------------|----------|
| SVM        | 0.8916    | 0.8999      | 0.8474      | 0.8741   |
| $k$-NN    | 0.9692    | 0.9797      | 0.9697      | 0.9694   |
| RF         | 0.9816    | 0.9738      | 0.9600      | 0.9730   |

| Classifier | Precision | Sensitivity | Specificity | Accuracy |
|------------|-----------|-------------|-------------|----------|
| SVM        | 0.8292    | 0.9193      | 0.8873      | 0.8526   |
| $k$-NN    | 0.9686    | 0.9714      | 0.9551      | 0.9634   |
| RF         | 0.9549    | 0.9568      | 0.9330      | 0.9464   |

| Classifier | Precision | Sensitivity | Specificity | Accuracy |
|------------|-----------|-------------|-------------|----------|
| SVM        | 0.8153    | 0.8551      | 0.7911      | 0.8056   |
| $k$-NN    | 0.9599    | 0.9649      | 0.9474      | 0.9549   |
| RF         | 0.9415    | 0.9425      | 0.9121      | 0.9298   |

| Classifier | Precision | Sensitivity | Specificity | Accuracy |
|------------|-----------|-------------|-------------|----------|
| SVM        | 0.9418    | 0.949       | 0.9239      | 0.9347   |
| $k$-NN    | 0.9874    | 0.9894      | 0.9839      | 0.9860   |
| RF         | 0.9855    | 0.9626      | 0.9396      | 0.9673   |

Performance and the generalization ability to avoid overfit, $C$ equal to 10 and $\gamma$ equal to 0.01 are adopted in the SVM classifier.

**C. SELECTION OF HRV FEATURES**

Different combinations of HRV features are used to train the classifiers, and the results are shown in Table 3. Table 3 shows that when time domain features or nonlinear features are used alone, the $k$-NN performs the best, whereas RF performs the best when frequency domain features are used alone. Same as that in Table 1, the bold style in Table 3 highlights the best values for each parameter. With more features are combinedly used in training, the performance is in general improved for all classifiers, although there could be mild fluctuations. Among the 3 classifiers, when time domain, frequency domain and nonlinear features are all used, the $k$-NN classifier steadily outperforms the other two; the four performance parameters achieved are all higher than 98%.

**D. DETERMINATION OF WINDOW LENGTH FOR HRV FEATURE EXTRACTION FROM ECG SIGNAL**

In Session IV, we stated that the window duration to compute the HRV features is set to 60 seconds. This is determined by the performance parameters shown in Fig. 6. The classifier is trained with HRV features extracted from different lengths of windows.

Window lengths from 15s to 120s are tested. In the range from 15s to 30s, the window lengths are increased by a step-size of 5s, whereas from 30s to 120s, the window lengths are increased with a step-size of 10s. In both cases, the window slides by one RR interval for the adjacent computation. The figures in Fig. 6 shows that the performance with longer window length is better than those with shorter window length, although the performance parameters are not increased monotonically.

However, longer window could not localize the instants that the subject is in a specific state for a short period. In addition, longer window also goes against the real-time processing. To tradeoff between the performance and the time localization, a window duration of 60 seconds is selected.

Through the data and training above, it is verified that $k$-NN classifier surfaced as a good classifier in the stress state identification using HRV features. In a short summary, the HRV features are extracted based on overlapped windows with 60-second duration. The value of $k$ is chosen to be 1, and all the features are used in the training of $k$-NN classifier. The performance parameters obtained in the verification stage, including precision, sensitivity, specification, and accuracy, are all exceeding 98%.

In the next two sections, the in-car experiments are described, and the ECG data collected will be predicted by using the trained $k$-NN classifier.

**VI. IN-CAR EXPERIMENT**

The in-car experiment is conducted to collect ECG data of subjects who is driving car when GPS navigation is in use. These data were collected in the preliminary study earlier [18], and re-used in this study. By analyzing the obtained data using the trained $k$-NN classifier, the stress state induced due to the GPS navigation is studied. The experiment is described again for the completeness of the research.

**A. EXPERIMENT OVERVIEW**

The driving protocol was designed to consist a route over about 5 kilometers in a community. The route was planned to contain many turns and to pass through some points of interest in order to activate the GPS instructions. Drivers were selected based on their answers to a questionnaire, and the shortlisted drivers were scheduled to drive along the pre-designed route using their own cars.

During driving, three types of information were collected 1) ECG signals of drivers, 2) Audio signals recording sound...
inside the car, and 3) Video signals recording road conditions around the car. To collect these data, three devices, i.e., ECG monitor, DashCam and GPS, were installed on the car before driving. Each driving test took about 50 to 70 minutes dependent on road conditions.

B. SUBJECTS AND QUESTIONNAIRE
The study group, consisting of 38 drivers between 20-65 years old, was selected based on the following criteria through a pre-experiment questionnaire: holding a valid driver’s license, being able to use GPS in English, at least one year driving experience at the time of experiment, and not suffering from any previously diagnosed cardiac or respiratory disorders. Each subject was informed in detail about the study, and consents to having video and ECG signals recorded during the drive were obtained prior to data collection. Before beginning, instructions, such as obeying speed limits, turning off their own GPS, and mobile devices, to keep the drives consistent, were given.

C. EQUIPMENT AND SETUP
In this experiment, a B20 Patient Monitor of GE Healthcare with sampling frequency of 300Hz was used to record ECG signal. Similar as B30, this model records ECG signals from III lead electrodes attached on chest. The recorded ECG signals were transmitted through a cable to a notebook in real-time for further processing.

Besides the patient monitor to record the ECG signals, GPS navigation tool with pre-loaded map was installed to provide navigation instructions. The GPS was chosen in the criteria that it could provide the features of setting multiple destinations along a route, and customized settings of different types of voice alerts. To record the whole experimental environment, including the voice alert from the GPS navigation system and the traffic condition around the car, a DashCam video camera was also installed.

Since both the audio and video signals are collected by the DashCam, these two signals are automatically synchronized. On the other hand, both signals collected by the patient monitor and DashCam contain time stamps, and these two devices are synchronized before the test to ensure the data synchronization.

D. PROCEDURES
All drives were conducted in mid-morning or mid-afternoon when the traffic was light on road. The 38 subjects are divided into 2 groups. In the first group, with subjects from 1 to 11, each subject was asked to drive two rounds following GPS instructions, one round with higher density of instructions, including full-street-name alert, turning-distance warning, point-of-interest report, and “turn now” instruction, and the other with lower density of instructions, including only turning alerts (like “turn left” or “turn right”) without alerts of full street name, turning distance, or point of interest. In the second group, with subjects from 12 to 38, each subject was also asked to drive two rounds for a given route, one round with GPS instructions, and the other without. A 5-minute break is given between the 2-round driving in both groups.

ECG signals of the drivers, videos of the road conditions and audios of GPS instructions were recorded during driving.

FIGURE 6. The performance parameters for different window lengths in (a) SVM, (b) k-NN, and (c) RF.
TABLE 4. Percentage of stress samples during different driving events.

| Group                      | Subject | Wait Mark | Turn Mark | Traffic Mark | GPS Mark |
|----------------------------|---------|-----------|-----------|--------------|----------|
| First Group: High vs. Low GPS Instruction Intensity | 1       | 85%       | 85%       | 88%          | 81%      |
|                            | 2       | 63%       | 85%       | 82%          | 75%      |
|                            | 3       | 36%       | 87%       | 49%          | 67%      |
|                            | 4       | 56%       | 75%       | 68%          | 79%      |
|                            | 5       | 71%       | 77%       | 84%          | 78%      |
|                            | 6       | 55%       | 61%       | 59%          | 62%      |
|                            | 7       | 72%       | 81%       | 80%          | 69%      |
|                            | 8       | 76%       | 64%       | 59%          | 78%      |
|                            | 9       | 67%       | 87%       | 78%          | 90%      |
|                            | 10      | 64%       | 89%       | 57%          | 80%      |
|                            | 11      | 61%       | 71%       | 57%          | 75%      |

| Second Group: With vs. Without GPS Instruction | 13      | 82%       | 79%       | 72%          | 76%      |
|                                             | 14      | 62%       | 85%       | 72%          | 81%      |
|                                             | 15      | 63%       | 80%       | 83%          | 79%      |
|                                             | 16      | 69%       | 80%       | 86%          | 78%      |
|                                             | 17      | 57%       | 81%       | 54%          | 75%      |
|                                             | 18      | 84%       | 89%       | 90%          | 91%      |
|                                             | 19      | 51%       | 82%       | 49%          | 84%      |
|                                             | 20      | 59%       | 86%       | 95%          | 78%      |
|                                             | 21      | 57%       | 89%       | 98%          | 97%      |
|                                             | 22      | 79%       | 79%       | 81%          | 83%      |
|                                             | 23      | 64%       | 88%       | 89%          | 84%      |
|                                             | 24      | 56%       | 91%       | 87%          | 94%      |
|                                             | 25      | 85%       | 75%       | 78%          | 81%      |
|                                             | 26      | 61%       | 80%       | 67%          | 86%      |
|                                             | 27      | 68%       | 82%       | 91%          | 93%      |
|                                             | 28      | 69%       | 74%       | 77%          | 46%      |
|                                             | 29      | 62%       | 97%       | 88%          | 92%      |
|                                             | 30      | 57%       | 81%       | 89%          | 87%      |
|                                             | 31      | 73%       | 87%       | 72%          | 84%      |
|                                             | 32      | 67%       | 98%       | 96%          | 91%      |
|                                             | 33      | 64%       | 82%       | 80%          | 92%      |
|                                             | 34      | 45%       | 82%       | 84%          | 71%      |
|                                             | 35      | 79%       | 80%       | 88%          | 69%      |
|                                             | 36      | 98%       | 99%       | 100%         | 95%      |

Average 66% 82% 78% 81%

VII. DATA PROCESSING

The ECG signal collected, based on the recorded audios and videos, are labeled with different event marks, including turning, waiting for traffic lights, GPS alert, and traffic conditions, such as overtaking or passing-by other cars. Meanwhile, the ECG signals are processed with the R-peak detection algorithms [28], [29] to extract the RR intervals. HRV features are computed in the way introduced in Session IV. The 60-second windows are applied to the data segments centered at the time instant that we are interested to detect. The $k$-NN classifier trained in session V is applied to predict whether the interested time instant is in stress state or relaxed state.

Table 4 shows the prediction results of samples classified by events. The data of 3 subjects, specifically subjects 12, 17 and 20, which are invalid because the data were corrupted heavily by noises for different reasons, are not included. The entries in the table indicate the percentage of time instants that the subject is in stress state during each type of events.

We can see that most people experienced a larger time-percentage of stress state than relaxed state during turning, other traffic conditions and under GPS instructions. It implies that for most of the time, the subjects are highly focused. Even during waiting event, most subjects are stressful during more than half time.

The last row is the total percentage of time that the subjects are in stress state during the specific event.

The comparison shows that turning is the most stressful event among the four events for the subjects. This is consistent with our common experience because drivers face the most complicated traffic conditions when turning. GPS instructions are in the second position to induce stress, with a higher percentage of time for subjects in stress state than that of other traffic conditions. This is partially because the other traffic conditions include not only relatively difficult ones such as overtaking or changing lanes, but also the relatively simple ones, such as other cars’ passing-by in the same or opposite directions.

Last, it is noted that during waiting events, most people had more than half time being in stress state. This is reasonable because the ground truth of relaxed state is the time that subjects are listening to music. However, during waiting time, drivers have to keep alert for all the time and react quickly when necessary. Compared with the state of listening to music, certainly waiting time shows a certain level of stress.

Tables 5 and 6 show the percentage of samples predicted to be in stress state during the entire driving route under different GPS instruction modes.

The data in Table 5 compares the cases with GPS instructions and without GPS instructions. It shows that all subjects in more than half of the time are in stress state in either case. As to the difference between the cases with and without GPS instructions, the results show high personal discrimination, i.e., some people have similar percentage of stress.
TABLE 6. Percentage of stress time during the entire round of driving—comparison of low vs. high GPS instruction intensities.

| Subject | Without GPS | With GPS | Percentage of Difference |
|---------|-------------|----------|-------------------------|
| 1       | 67.2%       | 62.3%    | 7.29%                   |
| 2       | 60.6%       | 58.5%    | 3.47%                   |
| 3       | 75.4%       | 57.9%    | 23.21%                  |
| 4       | 60.3%       | 52.4%    | 13.10%                  |
| 5       | 61.8%       | 56.1%    | 5.22%                   |
| 6       | 61.3%       | 53.7%    | 12.40%                  |
| 7       | 71.2%       | 60.2%    | 15.45%                  |
| 8       | 63.9%       | 69.7%    | -8.32%                  |
| 9       | 57.3%       | 60.3%    | -4.98%                  |
| 10      | 64.4%       | 70.6%    | -6.87%                  |
| 11      | 69.0%       | 60.8%    | 11.88%                  |

The results obtained above are interesting because most people may hold the view that GPS can help people drive easier or alleviate stress level when driving. However, the results show that some people may need to concentrate longer when more GPS instructions are provided.

VIII. CONCLUSION

In this paper, we investigate drivers’ stress state when GPS navigation is in use during driving. To achieve this objective, two experiments are performed. First, an in-laboratory experiment is designed to elicit subjects’ stress state by taking the SCWT. The ECG signal of the subjects are collected, to establish the relation between the stress/relaxed states and HRV features extracted from ECG signal by training three binary classifiers. The best classifier, k-NN classifier, was applied to the data collected in the second in-car experiment, where the ECG data were collected when the test subjects were driving under different GPS instruction modes.

The result shows that most people are stressful for more than 50% time during the GPS instruction. This implies that people need to concentrate more during the GPS instructions. And for the stress state of the whole driving period, some people may experience longer stress period with more GPS instructions whereas some others may experience shorter. It implies that GPS navigation can alleviate the stress condition for some people, but not for all; for some other people, with more GPS instruction in the whole driving period, they need more time to focus and could cause more tiredness.

REFERENCES

[1] R. G. Smart, E. Cannon, A. Howard, and P. Frise, “Can we design cars to prevent road rage?” Int. J. Vehicle Inf. Commun. Syst., vol. 1, nos. 1–2, pp. 44–45, Jan. 2005.
[2] I. C. Jeong, D. H. Lee, S. W. Park, J. I. Ko, and H. R. Yoon, “Automobile driver’s stress index provision system that utilizes electrocardiogram,” in Proc. IEEE Intell. Vehicles Symp., Istanbul, Turkey, Jun. 2007, pp. 652–656.
[3] R. W. Marans and C. Yoakam, “Accessing the acceptability of IVHS: Some preliminary results,” in Proc. Veh. Navigat. Inf. Syst. Conf., 1991, pp. 657–668.
[4] J. Healey and R. Picard, “SmartCar: Detecting driver stress,” in Proc. 15th Int. Conf. Pattern Recognit. (ICPR), Barcelona, Spain, 2000, pp. 218–221.
[5] H. Jebelli, M. Mahdi Khaliili, and S. Lee, “A continuously updated, computationally efficient stress recognition framework using electroencephalogram (EEG) by applying online multitask learning algorithms (OMTL),” IEEE J. Biomed. Health Inform., vol. 23, no. 5, pp. 1928–1939, Sep. 2019.
[6] P. Gaikwad and A. N. Patilhane, “Novel approach for stress recognition using EEG signal by SVM classifier,” in Proc. Int. Conf. Comput. Methodol. Commun. (ICCMC), Erode, India, Jul. 2017, pp. 967–971.
[7] F. A-Shargie, T. B. Tang, and M. Kiguchi, “Stress assessment based on decision fusion of EEG and HR signals,” IEEE Access, vol. 5, pp. 19889–19898, 2017, doi: 10.1109/ACCESS.2017.2753425.
[8] P. Karthekeyan, M. Murugappan, and S. Yaacob, “Detection of human stress using short-term ECG and HRV signals,” J. Mech. Med. Biol., vol. 13, no. 02, Apr. 2013, Art. no. 1350038.
[9] J. Fan, H. Li, Y. Zhan, and Y. Yu, “An electrocardiogram acquisition and analysis system for detection of human stress,” in Proc. 12th Int. Congr. Image Sign. Process., Biomed. Eng. Informat. (CISP-BMEI), Hangzhou, China, Oct. 2019, pp. 1–6.
[10] J. He, K. Li, X. Liao, P. Zhang, and N. Jiang, “Real-time detection of acute cognitive stress using a convolutional neural network from electrocardiographic signal,” IEEE Access, vol. 7, pp. 42710–42717, 2019, doi: 10.1109/ACCESS.2019.2907076.
[11] S. Bohnnithi and S. Phongsuphaph, “Comparison of heart rate variability measures for mental stress detection,” in Proc. Comput. Cardiot., Hangzhou, China, vol. 38, 2011, pp. 85–88.
[12] M. Elgendi and C. Menon, “Machine learning ranks ECG as an optimal wearable biosignal for assessing driving stress,” IEEE Access, vol. 8, pp. 34362–34374, 2020, doi: 10.1109/ACCESS.2020.2974933.
[13] J. A. Healey and R. W. Picard, “Detecting stress during real-world driving tasks using physiological sensors,” IEEE Trans. Intell. Transp. Syst., vol. 6, no. 2, pp. 156–166, Jun. 2005.
[14] G. Rigas, C. D. Katsis, P. Bougia, and D. I. Fotiadis, “A reasoning-based framework for car driver’s stress prediction,” in Proc. 16th Medit. Conf. Control Autom., Ajaccio, France, Jun. 2008, pp. 627–632.
[15] G. Rigas, Y. Goletsis, and D. I. Fotiadis, “Real-time Driver’s stress event detection,” IEEE Trans. Intell. Transport. Syst., vol. 13, no. 1, pp. 221–234, Mar. 2012.
[16] M. Manseer and A. Rienen, “Evaluation of driver stress while transiting road tunnels,” in Proc. 6th Int. Conf. Automot. User Interfaces Interact. Veh. Appl. (AutomotiveUI), Sep. 2014, pp. 1–6.
[17] A. Saeed and S. Trajanovski, “Personalized driver stress detection with multi-task neural networks using physiological signals,” in Proc. 31st Int. Conf. Neural Inf. Process. Syst. (NIPS), Long Beach, CA, USA, 2017, pp. 1–6.
[18] B. Z. Yang, K. Y. Eo, Q. Liu, G.-B. Huang, and Z. Lin, “Investigation on driver stress utilizing ECG signals with on-board navigation systems in use,” in Proc. 14th Int. Conf. Control Autom., Robot. Veh. (ICARCV), Phuket, Thailand, Nov. 2016, pp. 1–6.
[19] R. S. Lazarus and S. Folkman, Stress, Appraisal, and Coping, New York, NY, USA: Springer, 1984, p. 19.
[20] H. Selye, “The evolution of the stress concept: Stress and cardiovascular disease,” Amer. J. Cardiol., vol. 26, pp. 289–299, Sep. 1970.
[21] T. Esch, “Gesund im Stress: Der Wandel des Stresskonzeptes und seine Bedeutung für Prävention, Gesundheit und Lebensstil,” Gesundheitswesen, vol. 46, pp. 73–81, Feb. 2002.
[22] H. J. Baek, H. B. Lee, J. S. Kim, J. M. Choi, K. K. Kim, and K. S. Park, “Nonintrusive Biological signal monitoring in a car to evaluate a driver’s stress and health state,” Telemedicine J. E-Health, Off. J. Amer. Telemedicine Assoc., vol. 15, pp. 182–189, Mar. 2009.

time for the two cases, shown as shadow rows in Table 5, and the others present significant (> 5%) differences. More specifically, 8 persons are in stress state for longer time when no GPS is used, 5 persons are in stress state for longer time when GPS is used, whereas 11 others show no significant discrimination for the 2 cases.

Table 6 compares the cases where high intensity and low intensity of GPS instructions are provided. Similarly, the results show personal discrimination. However, significantly more people, specifically 7 people, have longer time in stress state when GPS gives less instructions, than 2 people who have longer time in stress state when GPS gives more instructions.

The results obtained above are interesting because most people may hold the view that GPS can help people drive easier or alleviate stress level when driving. However, the results show that some people may need to concentrate longer when more GPS instructions are provided.
[23] N. Skoluda, J. Strahler, W. Schlotz, L. Niederberger, S. Marques, S. Fischer, M. V. Thoma, C. Spoerri, U. Ehler, and U. M. Nater, “Intra-individual psychological and physiological responses to acute laboratory stressors of different intensity,” Psychoneuroendocrinology, vol. 51, pp. 227–236, Jan. 2015.

[24] L. Schwabe, L. Haddad, and H. Schachinger, “HPA axis activation by a socially evaluated cold-pressor test,” Psychoneuroendocrinology, vol. 33, no. 6, pp. 890–895, Jul. 2008.

[25] C. Kirschbaum, K. M. Pirke, and D. H. Hellhammer, “The ‘Trier Social Stress Test’—A tool for investigating psychobiological stress responses in a laboratory setting,” Neuropsychobiology, vol. 28, nos. 1–2, pp. 76–81, 1993.

[26] J. R. Stroop, “Studies of interference in serial verbal reactions,” J. Exp. Psychol. Gen., vol. 121, no. 1, pp. 15–23, Mar. 1992.

[27] J. Pan and W. J. Tompkins, “A real-time QRS detection algorithm,” IEEE Trans. Biomed. Eng., vol. BME-32, no. 3, pp. 230–236, Mar. 1985.

[28] J. Li and Y. J. Yu, “R-peak detection for ECG signal based on local maxima of signal magnitude and correlation,” in Proc. 12th Int. Congr. Image Signal Process., Biomed. Eng. Informat. (CISP-BMEI), Huaqiao, China, Oct. 2019, pp. 1–6.

[29] B.-S. Oh, L. Sun, C. S. Ahn, Y. K. Yeo, Y. Yang, N. Liu, and Z. Lin, “Extreme learning machine based mutual information estimation with application to time-series change-points detection,” Neurocomputing, vol. 261, pp. 204–216, Oct. 2017.

[30] P. Zontone, A. Affanni, R. Bernardini, A. Piras, and R. Rinaldo, “Stress detection through electrodermal activity (EDA) and electrocardiogram (ECG) analysis in car drivers,” in Proc. 27th Eur. Signal Process. Conf. (EUSIPCO), A Coruña, Spain, Sep. 2019, pp. 1–5.

[31] J. A. Healey, “Wearable and automotive systems for affect recognition from physiology,” Ph.D. dissertation, Dept. Elect. Eng. Comput. Sci., Massachusetts Inst. Technol., Cambridge, MA, USA, 2000.

[32] B.-S. Oh, Y. K. Yeo, F. Y. Wan, Y. Wen, Y. Yang, and Z. Lin, “Effects of noisy sounds on human stress using ECG signals: An empirical study,” in Proc. 10th Int. Conf. Inf., Commun. Signal Process. (ICICS), Singapore, Dec. 2015, pp. 1–5.

[33] P. Welch, “The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms,” IEEE Trans. Audio Electroacoustics, vol. 15, no. 2, pp. 70–73, Jun. 1967.

[34] J. Pan and W. J. Tompkins, “A real-time QRS detection algorithm,” IEEE Trans. Biomed. Eng., vol. BME-32, no. 3, pp. 230–236, Mar. 1985.

[35] C. Kirschbaum, K. M. Pirke, and D. H. Hellhammer, “The ‘Trier Social Stress Test’—A tool for investigating psychobiological stress responses in a laboratory setting,” Neuropsychobiology, vol. 28, nos. 1–2, pp. 76–81, 1993.

[36] J. R. Stroop, “Studies of interference in serial verbal reactions,” J. Exp. Psychol. Gen., vol. 121, no. 1, pp. 15–23, Mar. 1992.

[37] J. Pan and W. J. Tompkins, “A real-time QRS detection algorithm,” IEEE Trans. Biomed. Eng., vol. BME-32, no. 3, pp. 230–236, Mar. 1985.

[38] J. Li and Y. J. Yu, “R-peak detection for ECG signal based on local maxima of signal magnitude and correlation,” in Proc. 12th Int. Congr. Image Signal Process., Biomed. Eng. Informat. (CISP-BMEI), Huaqiao, China, Oct. 2019, pp. 1–6.

[39] B.-S. Oh, L. Sun, C. S. Ahn, Y. K. Yeo, Y. Yang, N. Liu, and Z. Lin, “Extreme learning machine based mutual information estimation with application to time-series change-points detection,” Neurocomputing, vol. 261, pp. 204–216, Oct. 2017.

[40] P. Zontone, A. Affanni, R. Bernardini, A. Piras, and R. Rinaldo, “Stress detection through electrodermal activity (EDA) and electrocardiogram (ECG) analysis in car drivers,” in Proc. 27th Eur. Signal Process. Conf. (EUSIPCO), A Coruña, Spain, Sep. 2019, pp. 1–5.

[41] J. A. Healey, “Wearable and automotive systems for affect recognition from physiology,” Ph.D. dissertation, Dept. Elect. Eng. Comput. Sci., Massachusetts Inst. Technol., Cambridge, MA, USA, 2000.

[42] B.-S. Oh, Y. K. Yeo, F. Y. Wan, Y. Wen, Y. Yang, and Z. Lin, “Effects of noisy sounds on human stress using ECG signals: An empirical study,” in Proc. 10th Int. Conf. Inf., Commun. Signal Process. (ICICS), Singapore, Dec. 2015, pp. 1–5.

[43] P. Welch, “The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms,” IEEE Trans. Audio Electroacoustics, vol. 15, no. 2, pp. 70–73, Jun. 1967.

[44] J. Piskorski and P. Guzik, “Geometry of the Poincaré plot of RR-intervals spectra: A method based on time averaging over short, modified periodograms,” IEEE Trans. Audio Electroacoustics, vol. 15, no. 2, pp. 70–73, Jun. 1967.

JINGBIN LI received the B.Eng. degree in information engineering from the Southern University of Science and Technology (SUSTech), Shenzhen, China, in 2018, and the M.Eng. degree in information and communication engineering. His research interests include signal processing and computer vision.

JIAHUI LV received the B.Eng. degree in information engineering from the Southern University of Science and Technology (SUSTech), Shenzhen, China, in 2018, where he is currently pursuing the M.Eng. degree in information and communication engineering. His research interests include signal processing and computer vision.

BEOM-SEOK OH (Member, IEEE) received the B.S. degree in computer science from Konkuk University, South Korea, in 2008, and the M.S. degree in biometrics and the Ph.D. degree in electrical and electronic engineering from Yonsei University, South Korea, in February 2010 and August 2015, respectively. From April 2015 to August 2019, he was a Research Fellow of the School of Electronic and Electrical Engineering, Nanyang Technological University, Singapore. He is currently an Assistant Professor with Gyeongsang National University, Jinju, South Korea. Prior to joining the GNU, he was an Assistant Professor with Tongmyong University, Busan, South Korea. His research interests include pattern analysis and classification, and machine learning.

ZHIPING LIN (Senior Member, IEEE) received the B.Eng. degree in control engineering from the South China Institute of Technology, Guangzhou, China, in 1982, and the Ph.D. degree in information engineering from the University of Cambridge, Cambridge, UK, in 1987.

He was with the University of Calgary, Canada, Shantou University, China, and DSO National Laboratories, Singapore, from 1987 to 1999. Since 1999, he has been with Nanyang Technological University (NTU), Singapore. His research interests include multidimensional systems and signal processing, statistical and biomedical signal processing, and machine learning.

Dr. Lin was a Distinguished Lecturer of the IEEE Circuits and Systems Society (CAS), from 2007 to 2008. He is a co-recipient of the 2007 Young Author Best Paper Award from the IEEE Signal Processing Society. He received several best paper awards at international conferences. He served as the Chair of the IEEE CAS Singapore Chapter, from 2007 to 2008 and in 2019. He was the Editor-in-Chief of Multidimensional Systems and Signal Processing, from 2011 to 2015, and has been serving on its editorial board, since 1993. He was an Associate Editor of the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS II: EXPRESS BRIEFS, from 2010 to 2011, and a Subject Editor of the Journal of The Franklin Institute, from 2015 to 2019.

YA JUN YU (Senior Member, IEEE) received the B.S. and M.Eng. degrees in biomedical engineering (BME) from Zhejiang University (ZJU), Hangzhou, China, in 1994 and 1997, respectively, and the Ph.D. degree in electrical and computer engineering (ECE) from the National University of Singapore (NUS), in 2004.

From 1997 to 1998, she was an Instructor with the Department of BME, ZJU. She became a Post-Master’s Fellow, and subsequently a Research Engineer with the NUS, from 1998 to 2004. Since 2004, she has been a Research Fellow of the Temasek Laboratory, Nanyang Technology University (NTU), Singapore. From 2005 to 2016, she was an Assistant Professor with the School of Electrical and Electronic Engineering, NTU. Since 2016, she has been an Associate Professor with the Department of Electrical and Electronic Engineering, Southern University of Science and Technology, Shenzhen, China. Her research interests include digital signal processing, biomedical signal processing, VLSI circuits, and system design.

Dr. Yu was served as an Associate Editor for Circuits, Systems, and Signal Processing, from 2009 to 2018, the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS II: EXPRESS BRIEFS, from 2010 to 2013, Digital Signal Processing (Elsevier), from 2015 to 2017, and the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS I: REGULAR PAPERS, from 2016 to 2019.