Platform for Safe Mobile Information Delivery

安全なモバイル情報配信のプラットフォーム

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The Safe Mobile Information Delivery platform dynamically detects the stress level of an automobile driver and uses that information to control mobile information delivery thereby reducing driver distraction during critical times. A static test environment was created to assess different stress detection algorithms. Frequency and time domain Heart Rate Variability (HRV) analysis enhanced by the Respiratory Frequency analysis is proven to provide the most accurate stress detection in a static environment. To validate performance in actual driving situations, a system was developed to collect and process dynamic driving data in real time to determine the driver's stress level.

本プラットフォームは，自動車ドライバーのストレスレベルをダイナミックに検知し，ストレスレベルに応じてモバイル機器からのユーザデータ配信を制限し，ドライバに対する危険な注意散漫要因を減らすことを目的とする。これを構築するに当たり，まず静的な試験環境において，周波数・時間領域での心拍数変動（HRV）分析，および呼吸レート分析の両者を用いたストレス検知アルゴリズムが，最良の結果を提供することを証明した。さらに，実環境でのドライバーのストレスレベルをリアルタイムに決定するシステムを設計，実装した。

1．Introduction

The vision of the Safe Mobile Information Delivery project is to provide a solution to dynamically detect the stress level of an automobile driver and use that information to reduce driver distraction from mobile data, such as alerts and notifications from a smart phone.

Stress affects the body's physiological state. The autonomic nervous system (ANS) is part of the peripheral nervous system that regulates the body's major physiologic activities, including heart rate and respiratory rate. The ANS has two branches: sympathetic nervous system (SNS) and parasympathetic nervous system (PNS). The SNS branch helps prepare the body for action in response to potential threats (stress). The PNS branch is most active under relaxed situations and brings the body to a rest state.

Studies have been done to identify physiological markers of stress detection. Many results indicate that Heart Rate (HR) and Heart Rate Variability (HRV) signals were significantly correlated to stress[1). As a result, the measure of cardiac activity becomes an ideal and non-invasive way to evaluate the state of ANS and determine stress level.

Developing a reliable stress detection algorithm is the first milestone for the Safe Mobile Information Delivery project. To achieve this, we created a static test environment to assess different stress detection algorithms. Using the static test environment, we collected data and tuned the stress detection algorithms. Then, we created a system to collect and process dynamic driving data in real time to determine the driver's stress level.

2．Static Environment and Analysis

We first created a static environment for data collection (Fig. 1). The static environment allowed us to collect biometric data in a controlled setting. We then evaluated various stress detection algorithms. Finally, we enhanced our algorithms in order to improve their accuracy.

2．1　Data Collection

2．1．1　Sensors

We use the Zephyr BioHarness 3 sensor. It is a compact physiological monitor module and incorporates Electrocardiogram (ECG) and breathing detection sensors.

2．1．2　Controlled Stimulus

We developed a PC based Controlled Stimulus application using PEBL. PEBL is an environment for designing and creating psychology experiments. Two widely utilized psychological or cognitive stressors are the Stroop color and

＊Mobile Communication Technologies, Sharp Laboratories of America, Inc.

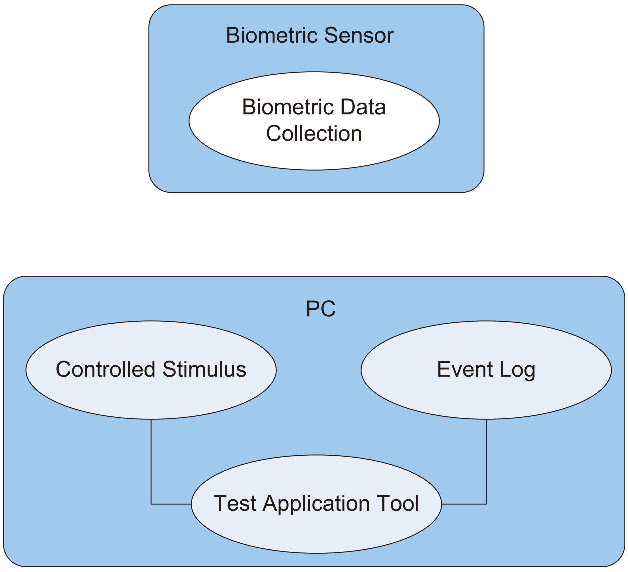

Fig. 1 Static Environment

mental math tests[2]. We enhanced PEBL's sample Stroop color and mental math scripts to increase the stress level. The enhancements include audio alert, error count, score animation and shortened response timeout. The result shows that the improved Stroop color and mental math test can serve as a stressor in the static environment.

2.1.3 Tools

We created a test application tool to be the control hub of the static test environment. It automates the test procedure and controls the duration and action of each test period. It also records the start and end time of each test period so that we can align the biometric log data from the sensor with the corresponding test period.

2.1.4 Experiment Protocol

11 healthy participants were monitored, 7 male and 4 female. Some of the participants performed the test more than once. Participants were given detailed instructions to attach the BioHarness 3 sensor before the test. Testing was performed in a room with low lighting. Participants sat comfortably in a chair in front of the testing laptop. In order to eliminate the effect of physical activity, participants were asked to minimize physical activities during the tests. To avoid other uncontrolled events, participants were asked to leave cell phones outside the test room. During the stress period, participants were required to give correct answer to as many questions as possible. The participant ran the test application tool on the testing laptop.

The test application tool controls the periods of relaxation and stress, as follows:

1. 1st relaxation period (15 minutes): Plays soft music while the laptop screen remains blank.
2. 1st stress period (10 minutes): Executes Stroop test or mental math test.
3. 2nd relaxation period (10 minutes): Recover period. Plays soft music while the laptop screen remains blank.

After the test, participants were asked to complete a questionnaire to identify the stress/relaxation level they encountered during various part of the test.

2.2 Data Analysis

2.2.1 Stress Detection Algorithm

Measuring cardiac activity is an ideal and non-invasive way to evaluate the state of the ANS and the stress level. In an ECG sample the RR interval refers to the time interval between two R peaks (Fig. 2). Heart rate variability (HRV) is the variation in the time interval between heartbeats. The most used HRV analysis involves time domain and frequency domain.

2.2.1.1 *Time Domain*

The time domain features include mean HR and mean RR and are usually considered a measure of physical workload. The frequency domain HRV is considered a mental workload measurement. However, for an individual who is performing light physical workload (such as driving a car), mean HR can also be sensitive to mental load[3].

2.2.1.2 *Frequency Domain*

HRV spectral analysis shows two important frequency bands: low frequency (LF) 0.04 − 0.15Hz and high frequency (HF) 0.15 − 0.4Hz[4]. Studies show that the power of the LF band results from the interplay between sympathetic and parasympathetic activity whereas the power of the HF band is the result of the parasympathetic control of the heart[3]. To isolate the effect of SNS and PNS, most researchers use the ratio of LF to HF (LF/HF) as an index of stress[2]. Higher LF/HF ratios indicate higher stress; lower LF/HF ratios indicate lower stress. We evaluated three most widely used frequency domain HRV analysis methods, including Welch method,

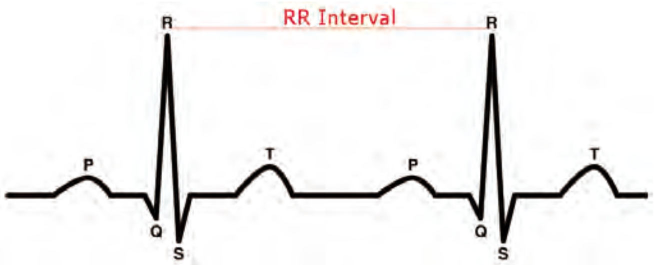

Fig. 2 ECG sample

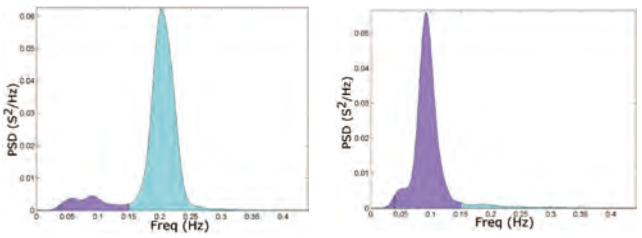

Fig. 3 Effects of slow breathing rate in the LF and HF band during a relax session. Relax with normal breathing, BR = 12.6/min (left), and relax with deep breathing, BR = 6.5/min (right)

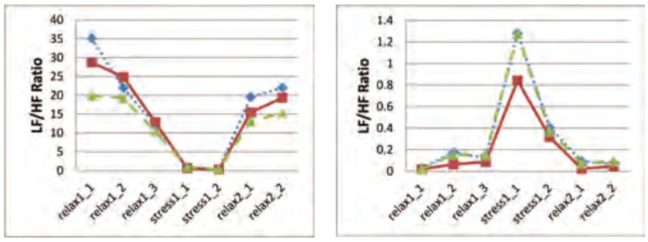

Fig. 4 LF/HF ratio before applying respiratory frequency (left), and after applying respiratory frequency (right). (dotted curve: Welch method, solid curve: Burg method, and dashed curve: Lomb-Scargle method)

Burg method, and Lomb-Scargle method.

2.2.1.3 *Effect of Respiration*

Respiratory sinus arrhythmias (RSA) are a cardiorespiratory phenomenon characterized by the HR or RR interval fluctuating with respiration. Usually, the heart rate increases during the inspiration and decreases during expiration. The respiration plays an important role in the heart rate and the parasympathetic activity is closely related to RSA.

Traditional HRV analysis uses a fixed frequency band for calculating power spectral density (PSD) in the LF and HF band. Slow breathing rate (BR) can cause an increase in the LF band power. This is a false-positive increase because it is caused by parasympathetic activity rather than the sympathetic (**Fig. 3**).

Our analysis of the data shows that the effect of respiration on HRV frequency domain analysis is too important to ignore. Instead of using fixed LF and HF bands, we implemented an enhanced HRV analysis that uses the respiration frequency (RF) to dynamically adjust the LF and HF bands. The HF range is from RF*0.65 to RF*1.35; LF range is from 0.04 to RF*0.65[5]. Our results demonstrate that this approach significantly improves the accuracy of the frequency domain HRV analysis (**Fig. 4**). After RF adjustment, all three algorithms successfully detect stress; whereas without the adjustment, all three algorithms produce false-positive high LF/HF ratios for the relaxation period, and low LF/HF ratios for the stress period. We also verified that RF adjustment does not adversely affect data collected during normal breathing.

2.2.2 Tools

Several tools are used in the post processing of the static data. The Zephyr BioHarness Log Downloader is used to download the log from the BioHarness 3 hardware to the PC; the Zephyr to Kubios File Converter is used to convert the RR file to the format that most HRV analysis software accepts.

HRVAS is an open source HRV analysis PC application developed using MATLAB. We used it as a baseline for our static analysis and algorithm evaluation. We added some enhancements to HRVAS including algorithms to address the effect of respiration on HRV analysis.

2.3 Static Result

2.3.1 Algorithm Evaluation

We evaluated three HRV frequency domain analysis algorithms, Welch method, Burg method, and Lomb-Scargle method. The following criteria was used to evaluate the algorithm,

- The last 5 minutes of relaxation was used as the baseline.
- The stress test has two 5-minute segments in the stress period. We considered the algorithm to have successfully detected the stress if there was a significant (>10%) jump in the LF/HF ratio, between the baseline and either of the two 5-minute segments.

There are 21 valid data sets. Based on the evaluation criteria mentioned above, the success rate for each algorithm to differentiate stress from relaxation is:

- Welch Method: 81%
- Burg Method: 67%
- Lomb-Scargle Method: 71%

2.3.2 Classify

We used the Weka 3.7.9 machine learning engine to train a classifier using different learning methods, including the J48 decision tree, Bayes Net, and Naive Bayes. From all of the static data, we picked 93 training instances. There were 37 with Stress ‘Yes’, and 56 with Stress ‘No’.

Biometric data such as heart rate are very much dependent on each individual’s initial physiological level. To eliminate those factors, the data sets needed to be normalized. We used the min max normalization process for each feature[2] so all the values fell between 0 and 1. The normalized values were fed to the classifier. **Fig. 5** shows the correctly classified instance rate with regard to different classifiers and different

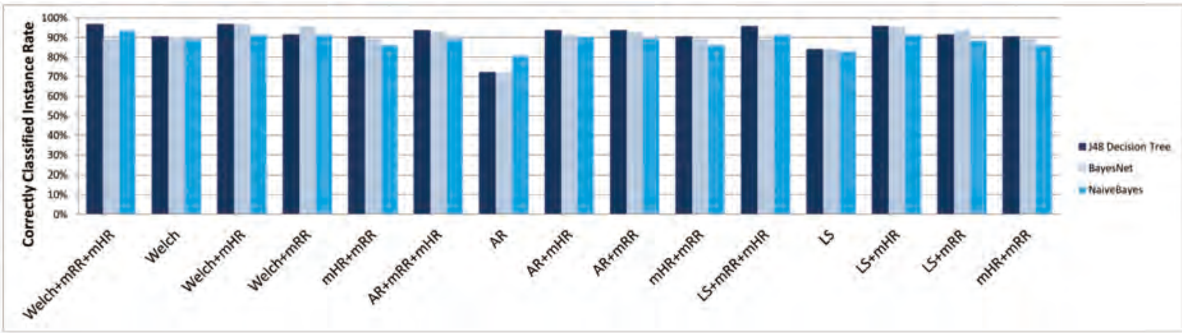

Fig. 5 Correctly classified instance rate. (Welch: Welch method, AR: Burg method, LS: Lomb-Scargle method, mRR: mean RR, mHR: mean HR)

combinations of features. We conclude that:

- Frequency domain (Welch method, Burg method, and Lomb-Scargle method) combined with time domain (mean HR, mean RR) performs better than only frequency domain or time domain.
- Overall, J48 decision tree performs better than the others.
- Welch related features perform better than the others

3. Dynamic Environment and Analysis

We developed a portable system to collect and process data in real time for the dynamic driving environment (Fig. 6). The system performs data collection and data analysis.

3.1 Data Collection

3.1.1 Data Acquisition Module

The center of the data collection is the Data Acquisition Module (Fig. 7). Running on an Arduino platform, the Data Acquisition Module collects biometric data and vehicle data. It has six keys to log external driving events, such as turn, lane change and traffic jam. It has an LCD panel to display real time RR, BR, and speed data. For portability, we designed a 3D printed enclosure for the Data Acquisition Module. The data collected by the Data Acquisition Module is transmitted to the Data Analysis Module in real time.

3.1.2 Experiment Protocol

Each drive test requires two people, a participant driver and an observer. The observer is to mark events that occur during the drive test. The observer also monitors the LCD display on the Data Acquisition Module to make sure that valid RR, BR, and speed are displayed.

At the time of this article, two drivers have participated in the drive test. The four sets of data collected proved the functionality of the Data Acquisition Module and dynamic

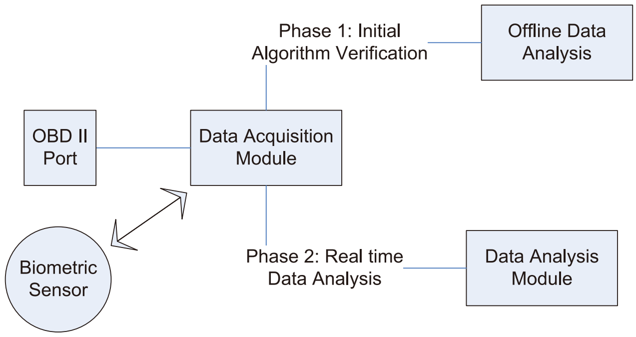

Fig. 6 System setup for dynamic driving environment

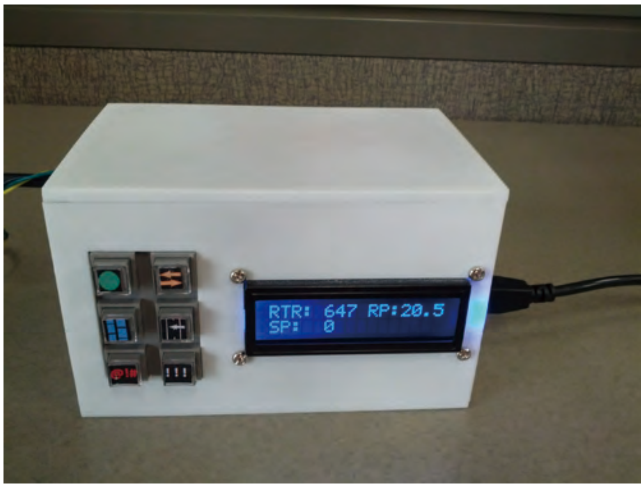

Fig. 7 Data Acquisition Module

drive experiment protocol. More participants and data samples are to be collected in the next phase of the project to further analyze stress in driving condition.

3.2 Data Analysis

Initially, we processed the data collected from the Data Acquisition Module using enhanced algorithms and tools developed during the Static Environment testing. We did this to verify the data collected from the Data Acquisition Module and to confirm that the algorithms developed during the

Static Environment testing could detect stress in a Dynamic Environment. We added additional features to the HRVAS application to analyze and display vehicle data and external driving events.

We then developed a real time Data Analysis Module using an ARM 11 application processor (Raspberry Pi). In real time, it processes collected biometric and vehicle data and determines whether the driver is suffering from mental stress. To do this, we ported the static test environment MATLAB algorithms to Python running on the Data Analysis Module.

HRV has been traditionally calculated from five minutes or more recording, however, the ultra short term HRV analysis[6)] shows that the shortest duration to identify stress from the baseline is 10 seconds for the time domain feature such as mean HR; 50 seconds for the frequency domain feature such as LF/HF. We average mean HR in a 10-s window and calculate frequency domain feature in a 60-s window.

The sample rate of the Vehicle data is 10Hz. We average the speed and acceleration using a 1-s window. Studies show that acceleration rates above 3-4m/s^2 are indicative of aggressive driving[7)]. Evidence suggests that aggressive driving produces higher levels of stress than normal driving[8)]. Thus, detection of aggressive driving could increase the speed and accuracy of our algorithms in determining stress.[9)]

4. Conclusion

We successfully created the static test environment, test protocol and collected samples to evaluate several frequency domain HRV analysis algorithms. During the data analysis, we further improved the algorithms to incorporate the respiration frequency data. This improvement has significantly increased stress detection accuracy especially during times of low respiration rate. From the 21 valid test sets, the best frequency domain algorithm, the Welch method, achieved 81% accuracy differentiating stress from the baseline. By combining time domain features with Welch method we have observed accuracies as high as 96.8%. The static analysis provides a good foundation for dynamic driving analysis. We successfully developed a real time data acquisition and analysis module for the dynamic driving environment and created a dynamic driving protocol and collected data.

In the next phase of the project, we will collect more data and improve the system and algorithms for dynamic environments to provide enhanced rejection of errors induced by electrical noise and missing data. We will also add an accelerometer and gyroscope to provide more precise vehicle data to the acquisition system. These will provide richer information about turns, movement, rotation, etc, which could help reveal driving style[10)] and accompanying mental stress. We hypothesize this information will improve our detection speed and accuracy. We will also study contactless biometric sensors to facilitate remote detection of biometric data from the driver.

With fast and accurate algorithms for detecting stress, we will be able to develop a platform for Safe Mobile Information Delivery, by controlling what information is displayed to the driver based on their stress level.

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