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Evaluation of Mental Stress and Heart Rate Variability Derived from Wrist-based Photoplethysmography

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Abstract

Heart Rate Variability (HRV) is a significant indicator of physical fitness and mental stresses. Electrocardiography (ECG) is the most common means to detect HRV. However, the nature of the ECG detection limits its convenience and usage time. While wrist-based Photoplethysmography (PPG) provides the possibility of convenient 24/7 HRV monitoring, its accuracy has not been systematically analyzed. We experimented with six healthy subjects and measured PPG from their wrist and ECG from their chest. The result shows that ten HRV parameters have significant differences between stress and non-stress states. Furthermore, the 10-fold accuracy of stress state detection within subjects is 98% and the Leave-One-Participant-Out F1 score reaches 80%. The results demonstrate that wrist-based PPG can provide HRV measurements that enable the recognition of mental stress as accurately as ECG, even for a short three-minute temporal window.

Key words: Wrist-based Photoplethysmography, Electrocardiography, Heart rate variability, mental stress

Introduction

Heart rate variability (HRV) is a significant health indicator for patients after acute myocardial infarction [1]. Monitoring of HRV has been proposed in healthcare areas such as heart diseases [2], diabetes [3], and mental health [4]. The usual practice of HRV measurement is conducted using electrocardiography (ECG) in a hospital setting. While an ambulatory measure of ECG can be conducted via a Holter device, it is often expensive and inconvenient to the human subject. Despite the needs of monitoring stress state, it is unrealistic and inflexible for psychologist or physicians to track our stress state throughout the day with an ECG device. Thus, a device that provides long-term stress-related data for patients and their doctors would be of great help.

HRV is also a common measure of human stress state, for it reveals the balance between the sympathetic and parasympathetic nervous system. When the sympathetic nervous system is triggered, and the parasympathetic system is suppressed, which is called fight-or-flight reaction, hormones epinephrine and nor-epinephrine would be secreted. This process evokes the increase of blood pressure (BP), heart rate (HR), muscle tension, skin conductance, and the decrease of HRV. When parasympathetic system is activated and sympathetic system is suppressed, which is called relax and digest process, the opposite physiological response as that of fight-or-flight process will be triggered [5][6].

Traditional HRV features could be divided into non-linear, time, and frequency domain measures. Typical non-linear domain features are SD1, SD2, and En (0.2) [7]. Mean RR (ms), SDRR (ms), RMSSD (ms), pNN50 (%) are popular time domain features [8]. The low frequency (LF) bands are related to sympathetic activity while high frequency (HF) bands are relevant to parasympathetic activity [9][10].

Generally, HRV features are generated from the successive R-R intervals of Electrocardiography (ECG). ECG is a standard heart rhythm measurement [11] and can track electrical impulses during the contraction and relaxation of the heart. Yet, Electrocardiograms are expensive and inconvenience because they are usually conducted in hospitals, and thus ECG is not suitable for everyday use.

Photoplethysmography (PPG) [12] is mainly based on optical tech: different living tissues and blood have different light-absorbing properties and thus different light reflection. PPG can also be a measurement of heart rhythm because the living tissues and blood properties will change during hearts contraction and relaxation in the force of blood flow. The advantages of PPG are that it is cheap and convenience and is a state-of-art and promising alternate of ECG. Yet, due to the motion artifact and huge noise in PPG signal, there is not much work working on detect stress state from wrist-based PPG.

In this research, we explore the possibility of using wrist-based PPG to detect HRV and compare it with the ground truth HRV detected by chest-based ECG. The results of individual and generalization stress prediction model provide strong support for wrist-based PPG.

Related Work

Birkett and Melissa [13] and Camm et al. [14] created standard for social stress test. To induce stress, Kirschbaum et al. [15] required subjects to subtract the number 13 from the number 1,022 serially. Each time the subject miscalculated, one member of the committee would ask the subject to restart at 1,022. Delaney et al. [16] and Endukuru et al. [17] produced psychological strain by conducting Stroop Word Color Conflict Test.

Castaldo et al. [18] and Kim et al. [19] conducted a Meta-Analysis on stress and HRV literature and suggested pooled

HRV measures including time, frequency, non-linear domain measures. Vollmer, Marcus [20] put forward a novel HRV feature named relative RRI.

Nitzan [21] is one of the early researchers that put forward the variability of PPG signals also have the potential of evaluating autonomic nervous system. Their experiment is up to 10 minutes long and is conducted on normal subjects and diabetic patients. In recent researches, Russoniello et al. [22] collected PPG using thumb sensor and ECG using wristbands sensors on both wrists from obese children. Three-five minute recordings of 11 HRV are calculated from PPG and ECG. Selvaraj et al. [23] captured ten subjects five minutes finger- tip PPG and ECG at rest. The evaluation shows that PPG from finger-tip has high correlation with ECG and there is no significant difference between PPG HRV and ECG HRV. Choi and Gutierrez-Osuna [24] used heart rate monitor to catch heart rate during one mental task and one relaxation exercise, and put forward a method called non-linear-principal dynamic modes for HRV analysis. Choi et al. ’s method reaches an 83% accuracy within subjects and 69% between subjects.

Our main contributions are to show that HRV measures derived from wrist-based PPG Green and IR signals have the potential to detect stress state as accurately as ECG. Also, we showed that small window size is enough for detecting stress state.

Methods

A. Data collection

We experimented with six healthy participants ages 21-40 years old. Participants are office employees that are familiar with the experiment environment. We measured PPG from their wrist and ECG from their chest using Polar H10. The subjects were guided to relax for ten minutes, performing mental arithmetic in the sight of an audience [15] for ten minutes and then relax again for ten minutes. All participants were asked to sit comfortably and keep movements at a minimum. We use Polar h10 to collect the ECG R-R intervals and use a wrist-band device to collect raw wrist-based PPG. The sampling rate of ECG and PPG are 100 Hz. There are three different LED light in the wrist-based sensors: Red, IR, and green light. In this experiment, we only used green and IR light because of their better quality compared with the red light.

B. ECG R-R intervals filter and PPG pre-processing

ECG signals are captured via the polar chest belt, and R- R intervals are transmitted via Bluetooth. The PPG signals captured via wrist positions are stored in internal memory and transferred to desktop computer for processing. A high- order Butterworth bandpass filter is adopted to filter the PPG signals. The challenges in PPG pre-processing of raw PPG collected from wrist-band includes low signal-to-noise ratio, severe baseline-drift, as well as motion artifact problems. Fig. 1 shows the raw PPG signal from the green channel. We can see that a very large trend or drift exist in the wrist PPG signal. Fig. 2 shows the bandpass filtered PPG signal. Occasionally, incorrect PP intervals are generated from noise corrupted signals. We designed rules for R-R Intervals and P-P intervals to drop intervals outside the range of 500-1200 ms.

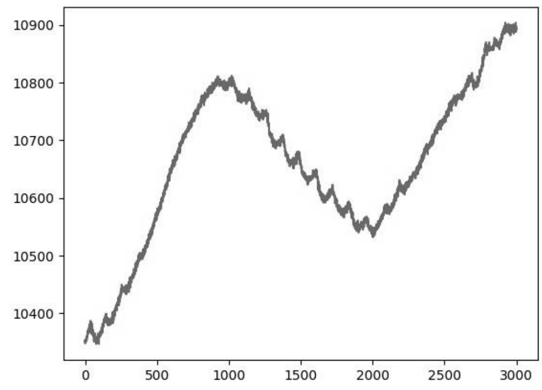

Fig. 1. Raw PPG waveform.

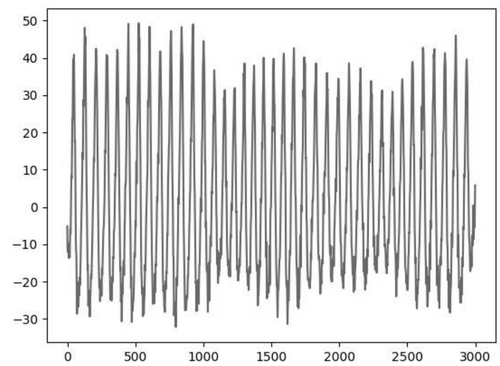

Fig. 2. Filtered PPG waveform.

C. HRV analysis

We then calculated 16 HRV features drawn from R-R Intervals and P-P intervals, shown in Fig. 3. Examples of the R-R Intervals for one subject is shown in Fig. 4. The RR interval has a scale of a millisecond. The spike in the figure could be the noisy measurement. We can see that at the beginning of the experiment, the subject has larger R-R intervals corresponding to slower heart-rate. As the experiment progress to the stress part, the R-R intervals drops significantly and then slowly rise after the stress part of the experiment finishes.

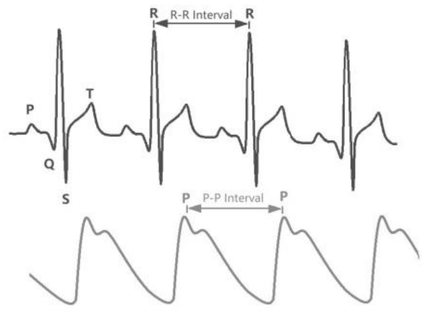

Fig. 3. ECG waveform and PPG waveform.

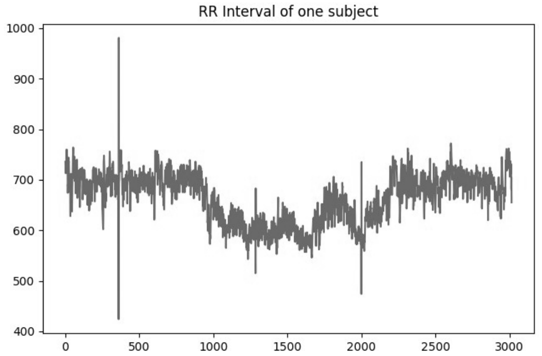

Fig. 4. R-R Interval of one subject.

For non-linear-domain parameters, we calculated short-term (SD1) and long-term HRV (SD2). For time-domain parameters, we calculated relative RR-Intervals, the number of interval differences of successive NN intervals larger than 50 ms (NN50), the proportion of NN50 divided by the total number of NN intervals (pNN50), root mean square of the standard deviation (RMS-SD), standard deviation of NN intervals (SDNN), mean heart rate (MHR), and mean RR interval (MRRI). For frequency-domain parameters, we calculated Total Power (TP), LF (0.04 to 0.15 Hz), HF (0.15 to 0.4 Hz), normalized LF (LFnorm), Very LF (VLF), normalized HF (HFnorm), and LF to HF Ratio (LF/ HF).

D. Stress detection using HRV

To analyze the performance of different PPG LED lights and the appropriate window sizes, we develop an individual stress prediction model for each scenario. We first used one minute, three minutes, and five minutes moving window with half overlapping to extract ten HRV features. Then we compared the performance of random forest classifier with that of SVM, Naive Bayes, and MLP model.

We chose ANOVA as hypothesis test model to see whether there is significant difference between HRV in stress state and HRV in non-stress state. $P < 0.05$ is considered statistically significant.

To build a generalization model to predict stress state, we used a standard scaler to scale the data and Leave-One-Participant-Out cross-validation to train and test data. We used RF as classification algorithm because it enables evaluation of the importance of significant feature, is fairly robust towards varying feature quality, and has strong model generalization ability. The evaluation metric is F1 score, the harmonic mean of the precision and recall of the classifier.

Results

The individual model using random forest algorithm has the best performance and its results of are presented in Table I. As we can see, both ECG and PPG reach a high accuracy using 3 or 5 minutes window size. Overall, green light is slightly better than IR and even better than ECG when using 3 and 5 minutes window size. Thus, in the following hypothesis test and generalization model, we only used PPG based on green light to compare with ECG, with 3 minutes and 5 minutes window size.

TABLE I
DETECT STRESS STATE-INDIVIDUAL MODEL

10-fold accuracy	ECG	IR	Green light
1min	90.07%	83.92%	84.52%
3mins	97.58%	96.29%	98.00%
5mins	97.94%	98.23%	98.48%

The results of hypothesis test are shown in Table II. Ten HRV parameters computed using RR intervals and PP intervals have significant differences between stress and non-stress states. HRV features like Mean heart rate, total power (TP), and low frequency (LF) bands show significant difference generated from both three minutes and five minutes window size, using both ECG and PPG datasets.

TABLE II
HRV HYPOTHESIS TEST.

HRV features	ECG (3mins)	ECG (5 mins)	Green Light (3mins)	Green Light (5mins)
SD1	0.075	0.085	**0.000102**	**3.69E-05**
SD2	0.374	**0.037**	**0.0031**	**7.17E-06**
RMSSD	0.075	0.086	**0.000102**	**3.70E-05**
SDNN	0.204	**0.044**	**0.000715**	**3.55E-06**
MHR	**1.83E-07**	**9.95E-09**	**0.027**	**0.0086**
MRRI	**8.83E-07**	**2.45E-08**	0.176	0.1
TP	**0.041**	**0.015**	**0.0028**	**3.94E-06**
VLF	0.932	**0.035**	**0.148**	**0.000275**
LF	**0.034**	**0.017**	**0.008**	**1.11E-06**
HF	**0.006**	0.265	**0.0017**	**7.25E-07**

The results of generalization model are shown in Table III. In stress state classification, our method achieves an overall Leave-One-Participant-Out F1 score of 80% in PPG dataset while the ground truth ECG reaches 79.7%. The results demonstrated that PPG can detect HRV and recognize the mental stress as accurate as ECG even in a short 3-min temporal window.

TABLE III
DETECT STRESS STATE-GENERALIZATION MODEL

Participants	ECG (5mins)	Green light (3mins)	Green light (5mins)
P1	0.86	0.96	1
P2	0.94	0.87	0.67
P3	0.94	0.96	0.92
P4	0.57	0.69	0.71
P5	0.86	0.5	0.8
P6	0.62	0.83	0.75
Overall	0.797	0.802	0.807

In Table I, Table II, and Table III, we observed that Green light PPG performs even slightly better than PPG. The reasons might be that raw RR intervals from polar have quality issues including the following: the loose contact of the electrodes with the subject's skin, some Bluetooth issues in the polar setup, some movement of the subject during the experiment.

Discussion

We have shown it is feasible to detect mental stress state using only wrist-based PPG HRV analysis. Our contributions are in three aspects: we study consumer-grade wrist-based PPG sensors, which is affordable, convenient, and with reason- able accuracy as consumer ECG sensors. For PPG signals, we suggest using green light rather than infrared (IR). Second, we find evidence to support that the three-minutes window is sufficient to identify stress mental state as induced by a math task as compared to a natural rest state. Lastly, we demonstrate the use of Machine Learning method to integrate HRV features for accurate stress detection. Further research enables mental stress detection in daily life, mental disease diagnosis, and assist the research about stress-related diseases like cardiovascular diseases and diabetes.

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