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cHRV Uncovering Daily Stress Dynamics Using Bio-Signal from Consumer Wearables

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Abstract

Knowing the dynamics of one's daily stress is essential to effective stress management in the context of smart and connected health. However, there lacks a practical and unobtrusive means to obtain real-time and longitudinal stress information. In this paper, we attempt to derive a convenient HRV-based (heart rate variability) biomarker named cHRV, which can be used to reliably reflect stress dynamics. cHRV's key advantage lies in its low maintenance and high practicality. It can be efficiently calculated only using data from photoplethysmography (PPG) sensors, the mainstream heart rate sensor embedded in most of the consumer wearables like Apple Watch. Benefiting from the proliferation of wearables, cHRV is ideal for day-to-day stress monitoring. To evaluate its feasibility and performance, we have conducted 14 in-lab controlled experiments. The result shows that the proposed cHRV has strong correlation with the stress dynamics (r>0.95), therefore exhibits great potential for continuous stress assessment.

Keywords:
Stress, Psychological; Biomarkers; Heart Rate

Introduction

Stress is a feeling of psychological and physical tension in reaction to a challenge or demand. We all have experienced stress from time to time, if not every day. In a nutshell, stress is hard-wired as an "alarm system." When our brain perceives threat, it signals our body to release stress hormones to prepare for the "fight-or-flight" response. Once the stressor is gone, the alarm system is meant to be reset so that our body can recover to a normal and relaxed state. Unfortunately, in modern life, the nonstop and pervasive stressors tend to always keep us on high alert, which over time, could lead to a broad range of health problems ranging from headache, depression to heart diseases [1-3]. This is why stress management is especially important more than ever, and it's needed everywhere, especially places with high concentration of stress such as workplace, classroom etc.

According to a national survey conducted by American Psychological Association in 2012 [4], Americans consistently report stress levels that exceed what they believe is healthy. Specifically, in 2012, approximately seven in ten Americans reported that they experienced physical or non-physical symptoms of stress, including irritability or anger, fatigue and changes in sleeping habits. What is more troubling is that the survey unveils the fact that people are struggling to manage their stress and tend to choose ineffective activities as their coping mechanism. For example, sixty-two percent of adults report that the activities they use to manage stress involve prolonged screen time, such as browsing the Internet, watching TV, playing video games and etc.

Despite the growing evidence of stress's epidemic impact on health, there still lacks practical solutions that offer support and proper intervention that help people navigate through their daily stress. This is largely due to the fact that there isn't a means to obtain people's daily stress dynamics in an unobtrusive manner. Measuring the levels of stress hormones, such as cortisol, is considered to be the "gold standard" and is able to provide an objective measure of stress level. However, it involves sampling and testing the subject's saliva or blood, which is invasive and time-consuming. Although providing accurate measurement, the result is only able to reflect only a snapshot rather than the dynamics of one's stress. Therefore, methods involving hormone testing are ill-suited for stress management.

In this paper, we propose a convenient HRV-based biomarker, (cHRV), that can be calculated only using photoplethysmography (PPG) data available in most consumer wearables. Due to its low maintenance and high practicality, cHRV bears great potential to make automated and personalized stress management possible. Not relying on custom devices other than a smartwatch, the computation of cHRV is designed to be passive and transparent to users with no extra cost, enabling a seamless integration into users' daily life. Moreover, cHRV offers a continuous and real-time stress signal, which is not only valuable at the individual level, but also powerful in generating insights about stress when examined at a higher level, for example, workplace, classroom and etc.

Specifically, in order to reliably reflect one's stress dynamics, cHRV is calculated using a number of physiological features based on heart rate variability (HRV), which is a commonly used indicator of Autonomic Nervous System (ANS) activities [5]. Studies show people under mental stress demonstrate a decrease in HF (high frequency) of HRV compared to a control group. Moreover, a sizeable body of research has also been dedicated to studying the link between HRV measurement and level of stress. The results suggest that HRV is a strong discriminative feature for distinguishing between stress and non-stress [6-8]. The changes in HRV is linked to the occurrence of stressors and is linked to each other due to the fact that the cardiovascular system is mostly regulated by the ANS through sympathetic and parasympathetic activities, which are also responsible for controlling body's reaction to subjective stressors. Therefore, HRV-based signals can offer insights into the activity of sympathetic and parasympathetic pathways, which in turn can reflect physiological stress in certain contexts.

The contributions of this paper are as follows:

- We propose a method of extracting a HRV-based biomarker (cHRV) from PPG that is reflective of the stress dynamics. The method is convenient and practical, and has great potential to offer support and proper intervention that help people navigate through their daily stress.
- We present the preliminary evaluation results that suggest the proposed biomarker is highly correlated with the stress dynamics.

Methods

The data collection was conducted in a controlled, in-lab setting. The primary goal of the experiment was to investigate the feasibility and effectiveness of using cHRV to capture stress dynamics. Therefore, all the experiments shared a fixed structure (shown in Figure 1) which was pre-defined to isolate and control the stressor that causes the stress.

Controlled In-lab Experiment

Figure 1 – Structure of controlled in-lab experiment

Setting

The experiments were performed in either office rooms or reserved meeting rooms where only one or two researchers and one subject were present. Prior to the experiment, the researchers will assist the subject with putting on the devices for data collection, and make sure data is being recorded properly. The devices used for recording physiological data include; 1) a wrist-worn device with PPG sensor and electrodermal activity sensor (EDA), 2) an electrocardiogram (ECG) sensor and 3) a headset with a 4-lead electroencephalogram (EEG) sensor.

Procedure

As shown in Figure 1, the in-lab experiment consists of 3 sessions including Baseline, Stress Test and Recovery. Specifically, during the Baseline session, we play guided meditation for 20 minutes to relax the subject as much as possible, in an attempt to minimize the residual stress from other prior stressors, if there is any. Therefore, the collected physiological signs at the end of the Baseline session should reflect the subject's baseline state (when not under stress).

In the Stress Test session, we conduct a standard stress-inducing test where the subject is requested to answer a verbally asked, non-trivial arithmetic question (e.g., 2010-37=?) every 10 seconds for about 6 mins [9-10]. This session consists of two such math tests with a 5-minute relax in between them to protect the subject from being under excessive stress. With the stress test, we exposed the subject to two types of typical daily stressors, which are 1) the stress as a result of being requested to solve non-trivial problems, and 2) the stress from having to finish tasks under time pressure.

In the Recovery session, we use the same relaxation technique as used in the Baseline session to help the subject recover from possible elevated stress. Data collected during this session will be used to investigate the recovery process from a stress buildup.

At the end of each session, we asked the subject to rate his or her current perceived stress level (**PSL**) on a scale from 0 to 10, with 0 being not stressed at all and 10 being extremely stressed.

Table 1 – List of Data Collection

Data	Sensor	Sampling Rate
PPG signal	PPG	64Hz
Skin Conductance	EDA	4 Hz
Brain Wave	EEG	250 Hz
Heart Rate	PPG	1 Hz
Acceleration	ACC	32 Hz
Perceived Stress Level	Self-report	n/a

Subjects

The subjects consist of 12 IBM employees, mostly composed of young adults with a few middle-aged subjects. Our study along with its data collection procedure is approved by the Institutional Review Board. All the subjects voluntarily agreed to contribute to the data collection and signed a consent form. Individuals will be excluded if they have significant health conditions or take medications that interfere with stress tasks including diagnosed cardiovascular conditions (e.g., arrhythmia, hypertension), neurological disorders (e.g., seizure disorder, stroke, transient ischemic attack), mental illness (e.g., depression, panic disorder) and cognitive or attention disorders (e.g., attention deficit/hyperactivity disorder).

Dataset

During the course of the experiment, we have collected a rich set of raw data from various sensors (shown in Table 1). For performance evaluation, we extracted cHRV along with three other signals commonly used as indicators of stress for comparison (shown in Figure 3).

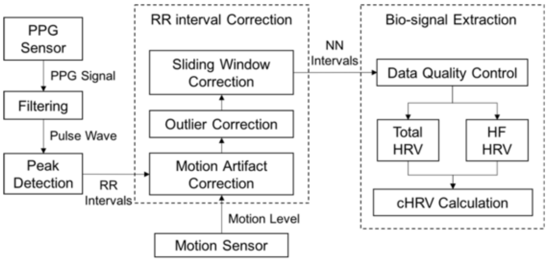

Figure 2 – A flowchart illustrating the process of extracting cHRV from consumer wearables

Extracting cHRV from PPG Signal

PPG sensor has been widely embedded in most smartwatches and fitness trackers. Similar to pulse oximeter, PPG is a light-based technology to sense the rate of blood flow as controlled by the heart's pumping action. As shown in Figure 2, A series of operations are involved in the process of extracting cHRV from consumer wearables with motion sensor and PPG sensor.

To calculate RR intervals from PPG signal, we first perform a 6-order Butterworth low-pass filter on the original PPG signal, with a cutoff frequency of 2 Hz. This filtering process is intended to filter out noise irrelevant to heart beats as much as possible. Then a peak detection operation will be conducted on the filtered PPG signal to identify peaks in the signal that represents heart beats. Lastly, the time intervals between successive identified peaks are extracted, resulting in a temporal sequence of RR intervals.

A sequence of outlier-free, beat-to-beat intervals is essential to accurate HRV calculation. In order to obtain normal and reliable RR intervals, commonly referred to as NN intervals, we filter out the outliers in RR intervals with a correction procedure consisting of three steps. First, as motion artifact is the major cause to corrupted PPG signal, we filter out the RR intervals based on their corresponding motion level, which is derived using acceleration data collected from the motion sensor. In the second step, a standard threshold-based method is used to filter out abnormal RR intervals based on its duration and also the difference in duration between consecutive RR intervals. Lastly, a distribution-based method is used to identify and remove outliers within a sliding window.

After the RR interval correction, the resulted sequence of the NN intervals will be used to extract cHRV. In clinical practice, no less than five minutes of NN intervals is required to calculate short-term HRV features, although recent research studies have suggested that shorter windows (e.g., 60 seconds) [11] may also be sufficient, especially for time-domain methods. In our case, a five minute sliding window of NN intervals are used to extract cHRV. To ensure the reliability of the feature extraction, a Data Quality Control component is responsible for identifying the window with a high percentage of discarded RR intervals, which is a major sign of poor data quality, mostly caused by excessive motion. Only data within windows, with acceptable data quality, are used to calculate HRV-based features. Features including the total power of HRV SDNN (standard deviation of normal to normal R-R intervals) and the high frequency power rMMSD (square root of the mean squared difference of successive N-N intervals) of HRV will be combined to calculate cHRV.

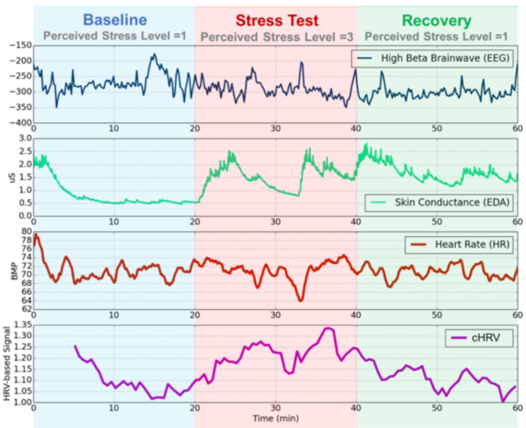

Figure 3 – Stress signals extracted from a 3-session in-lab experiments (from top: EEG, EDA, HR and cHRV signals), along with self-reported stress level at the end of each session.

Other Stress Signals Extracted for Comparison

To gauge the performance of cHRV in reflecting stress dynamics, we extract three other signals that are commonly used as indicators of stress and compare them with cHRV for evaluation purpose. Data used to extract these signals were all collected in paralell with the data used to derive cHRV. These stress signals include:

- Skin Conductance (**EDA**): The increase in EDA (Electrodermal Activity) signal indicates increased sweat production, which is commonly associated with sympathetic arousal.
- Power of high-beta band of the brain wave (**EEG**): increased power is associated with high arousal (e.g., stress and alertness)
- Heart Rate (**HR**): Certain stressful situations could lead to increased heart rate.

In Figure 3 we plot the cHRV signal along with the EDA, EEG and HR signals over time using data collected from a typical in-lab experiment. In these experiments, the subject's stress level has been successfully elevated by the Stress Test session and later relieved by the Recovery session, resulting in an increase of perceived stress level from 1 to 3 followed by a decline from 3 to 1. A key observation of this case is that the EDA and cHRV are the signals that most reflected the subject's stress dynamics. Specifically, a noticeable decline can be observed in both signals during the Baseline and Recovery sessions, which are designed to reduce previous stress and induced stress, respectively. More importantly, the increase in stress during the Stress Test session is clearly reflected in both EDA and cHRV. Interestingly, the effect of the short five minute resting in the middle of the Stress Test session is also captured, resulting in a brief dip around the thirtieth minute in both EDA and cHRV signals.

Results

The primary goal of the evaluation is to examine the cHRV's ability and effectiveness in reflecting the dynamics of stress. The basic idea is to examine the correlation between a signal and the stress dynamics during the experiment.

Perceived Stress Level

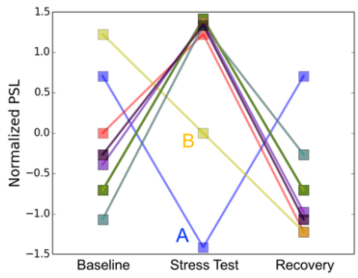

Figure 4 – Subjects' Perceived Stress Levels (PSL) during the in-lab experiment sessions (plotted with data from 14 experiments)

For evaluation purposes, we use Perceived Stress Level (PSL) as the proxy of the stress dynamics. PSL is reported by the subject at the end of each session on a scale from 0 to 10. The structure of our in-lab experiment was designed to see if the experiment showed a result in an PSL increase during the Stress Test session, and a PSL reduction after the Recovery session. In Figure 4, the normalized PSLs collected from 14 experiments are plotted over three sessions. Note that only two subjects' PSL reports are inconsistent with the structure of the experiment. Interestingly, one subject (A) reported reduced PSL in the Stress Test session (blue line Figure 4), although, all four stress signals suggest otherwise (blue lines Figure 5). Therefore we speculate that subject (A) might have a misperception of his or her stress level. Another subject (B) reported constant stress reduction (yellow line Figure 4) during the experiment. This could be largely because the subject began the experiment with relatively high residual stress built up from work or other previous activities, rendering the stress-inducing session ineffective. Although the Stress Test did not work as intended, the cHRV successfully captured data that showed a constant stress reduction over the experiment (the yellow line shown in Figure 5d).

Correlation-based evaluation

To investigate and demonstrate cHRV's effectiveness in reflecting stress dynamics, we calculate all four aforementioned stress signals' correlation with the subjects' perceived stress level for each of the experiments.

Specifically, we first conduct simple processing on the signal contained in each session, resulting in a sequence of three values for each signal. Due to inherent nature of the three sessions, the value is calculated by averaging the last five minutes of signals for Baseline and Recovery sessions, and the entire twenty minutes of signals for Stress Test session. Figure 5 shows the normalized result for each signal. Lines with the same color in Figure 4 and 5 represent data from the same experiment.

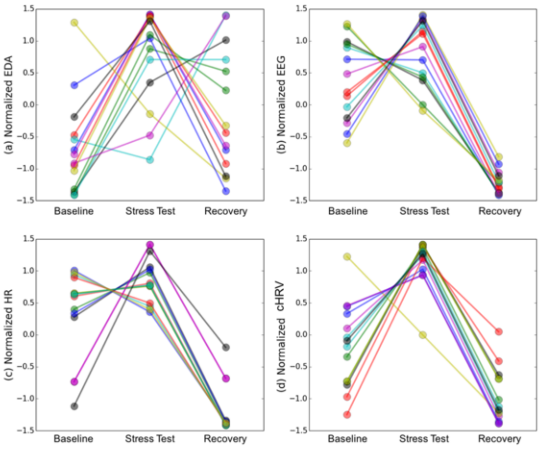

Figure 5 – Comparing cHRV with other signals in reflecting stress dynamics of 14 in-lab experiment.

Next, for each experiment, we calculate Pearson Correlation between the corresponding stress signal shown in Figure 5 and the reported PSL shown in Figure 4. The result is plotted in Figure 6. We can see that cHRV achieves the highest average correlation (r>0.95) with the most reliable performance. In contrast, other signals such as EDA and EEG failed in reflecting the stress dynamics, resulting in lower correlation with PSL. As we can see in Figure 5a, although EDA signal is able to capture the stress dynamics in most of the experiments, there are several results where the elevated stress in the Stress Test session were incorrectly measured as reduced stress. This could be mainly because that the skin conductance is also affected by other environmental factors such as room temperature, therefore adding uncertain noises. In Figure 5b, we can see that the EEG signal is accurate in detecting the decline in stress level in Recovery session, but tends to yield unreliable measurement for Baseline session.

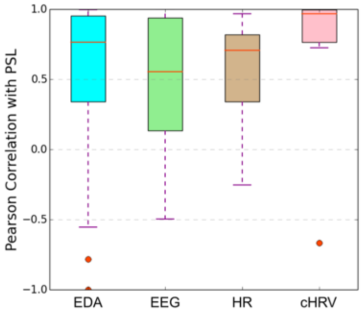

Figure 6 – Pearson Correlation (90 percentile) between 4 stress signals and the corresponding Perceived Stress Level.

Discussion

In this experiment, we use perceived stress level as the proxy stress indicator because there lacks ground truth on exactly how stressed people are. However, we have learned from the subjects that there may exist a gap between one's psycological perception of stress feeling and physiological measurement of stress response, as illustratd by Figure 4 that subject (A) might have a misperception of his or her stress level. To further probe this problem, we propose to categorize the perception-measurement levels into four groups, as shown below:

Figure 7 – Relationship between perceived stress level and measured stress level.

However, the current experiment is limited by the number and diversity of subjects. In the next phase of this study, we will recruit more subjects, then categorize them according to these four groups, and analyze for each group what charactoristics are representative and what factors or context contribute to the misperception (Groups 1 and 4). This line of research work will help us establish unique user stress profiles and identify influencing stressors and contexts. The goal is to provide in time, continous feedback to users so they have a better self understanding on how their minds and bodies function and respond to various stressors.

This is an essential step towards stress management. Our proposed cHRV method also offers a valuable objective addition to widely used psychological instruments for measuring self-reported perceived stress scales (PSS) [12] by providing real-time convenient physiological measures in daily life.

Another valuable insight gained from this experiment is that same physiological features could mean different stress indexes for different users, as shown in Figures 5 and 6. Therefore, one-size-fits-all detection model will not provide accurate and meaningful results for everyone. The proposed stress monitoring approach takes into account the individualized stress profile, which will be adjusted, using user's sparse stress labeling (e.g., users' perceived stress level at a certain time), so that it can gradually adapt to the user's unique physiological response.

Driven by the proliferation of wearable devices, the authors believe the ability to continuously monitor and manage stress in real-time is a critical component of this new exciting commercial domain. Although future studies are needed, the initial results of cHRV from PPG sensors, the mainstream heart rate sensor embedded in most of the consumer wearables, has shown its potential to not only enable researchers to explore practical, continuous, unobtrusive and personalized stress management, but also empower users to stay aware of their stress level in real-time and effectively and efficiently manage their stress on a daily basis.

Conclusion

In this study, we experiment practical and unobtrusive means to obtain real-time and longitudinal information about stress. The proposed cHRV approach uses proliferated consumer wearables to derive a convenient HRV-based biomarker to reflect daily stress dynamics. We compare and evaluate the feasibility and performance of cHRV through in-lab controlled experiments with other biosensors, including EEG, EDA and HR. The result shows that the proposed cHRV has strong correlation with the stress dynamic, and therefore exhibits great potential for continuous daily stress assessment with reasonable reliability and high practicality.

Acknowledgements

This experiment uses Empatica E4 wristband [13].

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