2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Classifying Heart Rate Variability Predicts Psychological Stress

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***Abstract*—Discriminating psychological stress (PS) in daily life based on passively sensed heart rate variability (HRV) is useful to monitor/manage PS in a constant manner with low burden. We classify PS levels from HRV continuously measured in daily life. Using a smartphone application and chest-mounted heart rate monitor, PS (6 times/day) and continuous HRV were obtained from ten participants over two weeks. A "gradient boosting classifier" was used to predict whether PS is higher or lower than the individual mean using HRV features in time intervals (~10, 30, 60 minutes) preceding PS measurement. Overall classification showed a high accuracy of 79%.**

I. Introduction

Psychological stress (PS) in daily life increases the risk of cardiovascular disease [1]. Previous studies on detecting PS from biometric data such as heart rate variability (HRV) have been typically conducted in restricted experimental environments with specifically designed stressors [1]. These findings cannot be generalized to daily life as PS responses to HRV fluctuate very quickly in response to real-life stressors and contexts. Here, we assessed PS and HRV in daily life over a two-week period and investigated the feasibility of predicting PS levels using HRV features.

II. Methods

All participants (6 males/4 females, age 21.1±1.1 years) were students at Shizuoka University, Japan, and free of medical issues or drug treatment. Participants wore Polar H10 devices (Polar Electro Oy, Kempele, Finland) on their chests to monitor RR intervals (RRI). Abnormal RRIs were manually inspected and corrected by the insertion/omission of missing/extra beats [2]. Two time (mean and SD of RRI) and 5 frequency domain measures were sequentially calculated for ~10-min segments of HRV (600 beats) every minute. After eliminating any linear trends every 10 minutes, fast Fourier transform analysis was used for 10-time-shifted subsets of 512 beats to obtain frequency domain measures [2]. The total power (TOT: >0.04 Hz) and the integrated spectral power in the low- (LF: 0.04–0.15 Hz) and high-frequency (HF: >0.15 Hz) ranges, the ratio of HF power to TOT, and the ratio of LF power to HF power (LF/HF) were calculated [3]. We also used physical activity counts and steps as features, which were simultaneously monitored by using an activity monitor (wGT3X-BT, ActiGraph LLC, Pensacola, FL, USA) due to the confounding effects that physical activity can have attenuating or exaggerating cardiovascular response [3]. To assess PS, participants rated their PS level on a Likert scale from 0-10 when notified by random alarm prompts 6 times/day, at about 2-hr intervals, on a smartphone application. PS level was classified as higher or lower than the individual average of all stress scores across the study period. HRV features averaged at time intervals (moving average for ~10, 30, and 60 min) prior to each PS measurement were used as explanatory variables to create a classifier model. The machine learning algorithm used was a gradient boosting classifier with Scikit-Learn [4]. Grid search was used for parameter tuning (results not shown), and the model was evaluated by cross-validation with 5 partitions.

This work was partially supported by Grant-in-Aid for Research Activity Start-up (19K24283, to J.K.) from the Ministry of Education, Culture, Sports, Science and Technology, and the BMBF through the e:Med Programme (031L0190A).

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III. Results

Classifier performance is shown in Table 1. Overall classification was promising with a high accuracy of 79%.

TABLE1. Proposed classifier performance based on untrained test data.

Performance Indicators	**Accuracy**	**Precision**	**Recall**	**F-measure**
Value	79%	76%	74%	75%

Note. Macro average of evaluation indices was used for each class.

IV. Discussion & Conclusion

HRV features accurately predicted PS levels, suggesting acute (~1h) cardiovascular responses to PS in daily life. Using ambulatory heart rate sensors to predict psychological stress with higher granularity and low burden may enable the application of these findings towards timing interventions for psychological stress relief.

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