The Accuracy of Monitoring Stress from Wearable Devices

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Introduction

Continuous monitoring of behaviors as well as physiological and mental states is increasingly considered to be a key prerequisite for optimizing health interventions. The recent influx of affordable wearable sensors may enable continuous and unobtrusive assessment of individuals' health in ambulatory settings. If such sensors provide data of sufficient quality, we will be better equipped to help individuals improve or maintain quality of life.

Stress has important implications for a wide variety of health conditions[1]. Hence, there is a clear need for new tools to monitor stress in real time to provide tailored and timely interventions. Although feasible in a clinical setting, ambulatory stress monitoring (ASM) still proves challenging. Even short instruments, like the 10-item Perceived Stress Scale, would be too burdensome for patients to complete multiple times a day. Of great promise in ASM are heart rate variability (HRV) and electrodermal activity (EDA). While numerous studies demonstrated that HRV and EDA are biomarkers of stress and emotion regulation[2], relatively few have attempted to use such data obtained from wrist sensors in ASM. As the efficacy of this data capture method hinges upon the quality of obtained measurements, the focus of this poster is on assessing the quality of data collected by two wrist sensors and proposing new algorithms to improve it enough for these sensors to be viable sources of ASM data.

Study design

Physiological data was collected in a laboratory setting using Firstbeat Bodyguard 2 (FB) (interbeat intervals, or IBI), Microsoft Band 2 (MB) (IBI, EDA), Empatica E4 (IBI, EDA), and J&J Engineering I-330-C2+ instrument (EDA). IBI were collected using pulse photoplethysmography sensors (MB and E4) and ECG chest electrodes (FB). Eight participants were led through cycles of relaxation (listening to relaxing music in a dark, quiet room) and stress (viewing International Affective Picture System photos, performing Stroop and mental arithmetic tasks, and engaging in physical exercise) to elicit physiological changes.

Results

Our preliminary results suggest that despite a significant degree of agreement between HRV data collected by wrist sensors and an ECG sensor in a laboratory, there is a relatively high level of dependency of the inferences on context and activity levels. To attenuate these effects, we developed an algorithm based on generative-model that uses singular spectrum analysis (SSA) of the RR interval sequence to separate the low-frequency components of HRV from the disturbances due movements as recorded by the accelerometers. SSA method generates a Toeplitz matrix from the RR sequences and then computes four principal components with the highest eigenvalues. We will describe this analytic process that makes it possible to fuse the accelerometry and the photo plethysmographic data to improve data accuracy. This poster will describe these novel approaches for extracting more precise stress information from noisy bio-signals. We will discuss the advantages of the model-based algorithms in capturing individual-level trends and differences in HRV and EDA over traditional population-based approaches.

Conclusion

Data collected by wearable sensors in a laboratory setting are of high quality, but new algorithms are required to make them useful for ambulatory stress monitoring.

References

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