WatchPPG: An Open-Source Toolkit for PPG-based Stress Detection using Off-the-shelf Smartwatches

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ABSTRACT

We present WatchPPG, an open-source toolkit that enables raw photoplethysmography (PPG) data collection and stress detection using off-the-shelf smartwatches.

KEYWORDS

Stress Detection; Commercial Wearables; JIT Intervention

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1 INTRODUCTION

There has been a growing interest in developing just-in-time (JIT) stress intervention systems that offer continuous in-situ stress monitoring to deliver interventions proactively [2, 3]. Evaluating such systems in a practical setting is critical to ensuring the ecological validity of intervention design [4, 5] and to improving the usability and user experiences of the systems. However, we identified a lack of an open-source toolkit using affordable wearable devices for such studies. To address this, we introduce the WatchPPG toolkit, focusing on heart rate variability (HRV) as a stress indicator. Our toolkit offers a WearOS application for raw PPG data collection, a convenient alternative to chest-worn electrocardiogram (ECG) devices, and a stress detection pipeline. We tested its viability using a Samsung Galaxy Watch and comparing the performance with ECG (Polar H10), and research-grade PPG (Empatica E4) devices. Data was collected in semi-naturalistic, stressful environments, and our results confirm the use of WatchPPG in various stress intervention studies.

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2 WATCHPPG PIPELINE AND EVALUATION

Pipeline: We present a PPG-based stress detection modeling pipeline. The entire analysis process, written in Python, along with the commercial wearable device application written in Kotlin, can be accessed via this link. Data preprocessing initiates the filtering process; a 0.8-3.5Hz Butterworth bandpass filter was used to eliminate non-heart rate frequencies and outliers were substituted with median values. This is followed by detecting peaks in raw signals to compute peak-to-peak intervals. We adopted a recently proposed algorithm called HeartPy [11], but our data analysis revealed significant errors due to motion-related artifacts [6, 8]. Consequently, we incorporated additional correction steps into HeartPy by implementing a chunk-based correction method on 4-second segments; removing and imputing values deviating over 150ms from the previous chunk mean [1]. We also applied median filter-based correction, replacing intervals differing more than 150ms from the filtered intervals with cubic spline interpolated values [10]. After peak detection, we then extract well-known time and frequency domain HRV features and build stress detection models using various machine learning models such as random forest and XGBoost [7].

Evaluation: We ran an approved study on 12 experienced emotion workers from call centers who wore the aforementioned one ECG and two PPG devices for data collection. The study involved a 4-minute baseline state—2 minutes of rest followed by 2 minutes of typing—and a 4-minute simulated call. The call scenario was adapted from the Trier Social Stress Test (TSST) [9] and involved a professional actor enacting a customer service issue. Participants were asked to stay polite regardless of what the actor said and summarize the session through the computer concurrently. We considered a binary classification task, designating the baseline as non-stress and the call as stress, and extracted HRV features every 60 seconds with a shift of 0.25 seconds [9]. The RF model showed accuracies of 80.3, 76.4, and 82.8 on Polar H10, Galaxy Watch, and E4, respectively, while XGBoost showed accuracies of 86.4, 76.7, and 81.8. The commercial watch and proposed pipeline had comparable detection performance to the ECG and research PPG devices.

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