StressBal: Personalized Just-in-time Stress Intervention with Wearable and Phone Sensing

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ABSTRACT

This paper proposes StressBal, a mobile system that offers personalized just-in-time stress intervention with mobile and wearable sensing. The system runs entirely on-device, detecting stress in real-time and providing respiratory exercise-based interventions. It also updates the stress detection algorithm continuously, based on user feedback. We envision an open mobile platform that helps researchers to design and evaluate automatic, seamless, and unobtrusive stress interventions during everyday activities.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Stress Detection; Stress Intervention; Just-in-time Intervention; Mobile and Wearable Computing

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1 INTRODUCTION

The stress of daily life has become an important issue in modern society. Both acute and chronic stress have noticeable effects on human health, including sleep disorders, headaches, depression, and cardiovascular disease. To avoid long-term consequences of stress, identifying stressful situations and managing stress in the early stage is required [3].

Stress management systems using passive sensing technologies such as wearable devices and smartphones have been extensively studied in the human-computer interaction fields. Physiological signals (e.g., heart rate, electrodermal activity) and behavioral data (e.g., body movements, mobile phone usage) are commonly used for detection [3], and mobile applications or interfaces for alleviating stress were presented (e.g., MindScope [5] and Stress@work [1]). Recent studies further explored a real-time management system [4]. However, there is a lack of open platforms that are based on commercial smartwatch and smartphone.

With such background, we propose StressBal, an unobtrusive mobile system that detects daily stress and provides just-in-time intervention using multimodal data and a machine-learning (ML) algorithm. The key contributions of this work are summarized as follows: (1) use of a commercial off-the-shelf wearable device for real-time data collection, (2) implementation of an adaptive stress recognition module that performs continual machine learning based on user feedback on a mobile phone, and (3) localized data processing enabled by complete on-device operations for privacy preservation.

2 SYSTEM ARCHITECTURE

Figure 1a shows the overall architecture of StressBal, and it consists of four modules: *Data Collection*, *Feature Extraction*, *Just-in-time Intervention*, and *Model Update*. We used *Garmin Forerunner 55* [1] and Android phones with operating system version 8.0 or higher. *Garmin Forerunner 55* was adopted due to its longevity, and the following describes each phase in detail.

Data Collection: During the configured time span (e.g., 10.30 to 22.30), we collect data from both smartwatch and mobile phone. *Garmin Forerunner 55* is equipped with sensors to measure inter-beat interval (IBI) and 3-axis accelerometer data (ACC). Using the Connect IQ SDK provided by *Garmin*, a maximum of 30-second sensor data can be transmitted to the mobile phone once every 5 minutes. Accordingly, 30-second IBI values and 5-second ACC (20Hz) values were recorded. ACC records were limited to 5 seconds, as similar window sizes are broadly applied for acceleration-based recognition [8]. Activity data, which are step counts and distance moved during the day, are simultaneously read from the watch. All the recorded values and read data are transmitted to the mobile phone at once through Bluetooth Low Energy. For the Android

[1] https://www.garmin.com/en-US/p/741137

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(a) Overall Architecture **(b) System User Interface**

Figure 1: Personalized just-in-time stress intervention system, StressBal

phone, we collect location and phone usage information. GPS coordinates (*i.e.,* longitude and latitude) and screen status (*i.e.,* ON/OFF) are stored. StressBal collects user feedback via Ecological Momentary Assessments (EMAs) every 2 hours. A Likert scale rating is used [6], ranging from very slightly or not at all to extremely as shown in Figure 1b. The answers are binned according to the following criteria: Quite a bit and Extremely to *stressed*, the others to *not stressed*, and they are used as ground truth for the user's current stress status in *Just-in-time Intervention* and *Model Update*.

Feature Extraction: Numerical and boolean features are extracted each time the watch data is transmitted (*i.e.,* once every 5 minutes). From the raw IBI values, heart rate variability (HRV) is calculated, using the root-mean-square of successive differences (RMSSD). From the raw ACC values, the mean, standard deviation, and magnitude for each axis are computed. From the step counts data, the number of steps taken in the past 5 minutes is extracted by calculating the difference from the previous data. From the distance data, whether the user has moved during the last 5 minutes is extracted by setting 10 meters as a threshold. GPS coordinates were processed to check whether a user is near *home* or at *work* whose coordinates were provided by the participants, and a threshold of 100 meters was used for place detection [2]. For screen status data, the time participants used their phones during the past 5 minutes was calculated. For simplicity, a total of 15 extracted features were used as input for the stress detection model.

Just-in-time Intervention: The system detects opportune moments to send a push notification for timely intervention, using the ML-based stress detection model. The model should be pre-trained with individual data in order to be used on a mobile device. As in the previous study [7], we consider the duration of the stress event as 20 minutes and label the EMA answer at time point X as the ground truth of extracted features from $X - 10$ min to $X + 10$ min. The baseline model is fitted with labeled data and deployed to the system using *Tensorflow Lite* for fully on-device operation. Once every 20 minutes (except when the EMA notification is sent), the system determines whether the user is stressed and sends a notification (only when a stress status is predicted). To predict the status at time point Y, data from $Y - 10$ min to Y is used as model input. The overall timeline of the data labeling and intervention process is shown in the upper right of Figure 1a. The intervention module follows the guidelines of the existing peripheral breathing exercise, which is known to be effective in stress management while being able to perform another primary task [9]. Actionable coaching guides breathing by displaying a simple message *Inhale and Exhale slowly* along with intuitive visualization. A green sphere with a timer in the middle turns red after 8 seconds, and at the same time, a message for user's interruption recovery *Now, Go back to your work* is displayed. The related user interface is shown in Figure 1b.

Model Update: The stress detection model used during *Just-in-time Intervention* is continuously updated on-device. As in the model pre-training step, the EMA answer at time point X is labeled as ground truth for data from $X - 10$ min to $X + 10$ min. Based on one-day EMA answers and corresponding data, the system retrains the model nightly. This allows the system to perform more accurate and personalized stress detection, and can also be implemented through *Tensorflow Lite.*

3 FUTURE WORK

StressBal has the potential to be utilized in various studies related to stress intervention in the wild. Future work could be done by evaluating the system in a specific environment and target user or by improving the detection algorithm (e.g., adopting reinforcement learning, adding other types of mobile data). Our plan is to release the system as an open platform to facilitate in-the-wild user studies.

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