WildStress: exploring rich situational contexts for stress detection in the wild

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***Abstract*—Short-term experience of stress arousal can be useful in coping with everyday life tasks. However, undergoing intense stressful scenarios frequently and consistently can be damaging for mental and physical health. To detect such stressful scenarios physiological stress models were developed in lab conditions, but still showed poor results in daily life settings. Hence, leveraging rich contextual information about user's daily life can help identify stress in uncontrolled daily life environments. To that end, this work details on our research direction, that is to use rich contextual data captured from users' daily lives alongside physiological readings to timely detect in the wild stress.**

***Index Terms*—stress, context, smartwatch, smartphone, mHealth, ubiquitous computing**

I. Introduction

Stress is body's response to internal or external stimuli recognized as detrimental [1]. Physiologically, it is a process that includes perception of a stressor via sensory inputs such as eyes and ears, release of a stress hormone (cortisol) in veins, and changes in our heart activity. While acute stress can help boost our performance in performing daily-life tasks, frequently experiencing intense stressful scenarios can have damaging effects in our health [2].

Physiological aspect of stress is well-studied using validated stressors (e.g., math test, cold pressor) in laboratory settings. Previous works have shown that physiological responses can vary across stressors [2]. This is a limitation for physiological stress models trained in lab-controlled settings when applied to in the wild scenarios. That can be due to the limited range of stressors covered in lab as opposed to broad range of possible stressors in everyday life. One of common approaches from here is to use contextual information to estimate perceived stress, which can lead to a more dependable stress detection accuracy in the wild.

Situational contexts in the wild can be utilized to evaluate the perceived stress – the level of appraisal of an event as stressful subjectively measured by a user. To that end, [3] has showed the effectiveness of 'high level' context (9 types of activity and time) in perceived stress detection in daily life settings. However, they could only achieve an F1 score of 0.613 using the high-level contextual information. Therefore, we plan to achieve a reliable accuracy for stress detection by enhancing the richness of the captured contextual information and carefully engineering physiological stress arousal information.

Previous work [4] conducted a three-week study on situational contexts in which they collected free-text responses on users' locations, social settings, and ongoing tasks (i.e. activity). Using the collected data, they developed a coding scheme for categorizing contextual factors that include 13 different categories for ongoing tasks, 2 for social settings, and 5 for location. We intend to use the contextual information defined in [4] added to the hour of day and day of week from [3]. We further elaborate on the contextual and physiological sensing data in the next section.

II. Data collection

We plan to accurately detect stress in the wild by leveraging contextual information to accurately capture perceived stress alongside physiological readings to consider the physiological aspect as well. Below we detail on our plans for the data and the data collection methods, followed by insights and details on the implementation of our data collection software we prepared for our future study.

A. Data types

We aim to collect (1) raw Photoplethysmography sensor readings, (2) tri-axial accelerometer readings, and (3) off-body detection results from a smartwatch. Peak-to-peak interval readings can be estimated using the raw PPG (i.e., Blood Volume Pulse) signals. To that end, acceleration readings are used to filter out activity confounds and inaccurate PPG readings. Off-body detection data can denote the windows of data when sensor is likely not touching the wrist skin, hence, helps ensure collection of valid PPG readings.

Alongside the physiological data, we plan to collect Ecological Momentary Assessment (EMA) data using smartphone. Throughout the day, we trigger push notifications 12 times a day anytime between 9am until 9pm, where the delay between consecutive EMA prompts is selected randomly between 40 to 80 minutes. Each EMA prompt follows with 8 questions. (1) four questions from PSS-4 [5] item questionnaire regarding users' momentary feelings and thoughts, (2) one 5-point Likert scale item on stress level, (3) social settings, (3) location, and lastly (4) the ongoing activity. The list of data can be seen on Table 2.

B. Data collection software

We developed a data collection software for latest Samsung Watch smartwatches running on WearOS , that continuously

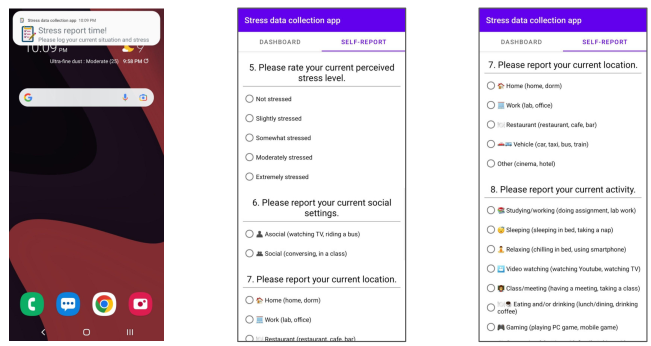
TABLE I
PHYSIOLOGICAL SENSING DATA FROM SMARTWATCH

Data	Sensor	Sampling rate
Heart activity	Photoplethysmography (PPG)	50Hz
Wrist motion	Accelerometer	12Hz
Off-body	Low-power off-body detector	12Hz

TABLE II
PERCEIVED STRESS LEVEL AND SITUATIONAL CONTEXT DATA COLLECTED USING SMARTPHONE EMA QUESTIONNAIRE APP

Data	Question	Answer option
PSS-4	(1) Control, (2) Confident, (3) YourWay, (4) and Difficulties	0-4 likert scale
Stress level	Current stress level	0-4 likert scale
Social settings	Current social settings	Social or Asocial
Location	Current location	Home, work restaurant, vehicle, other
Activity	Ongoing task / activity	Working/studying, sleeping, resting, video watching, in class/meeting, eating/drinking, gaming, conversing, going to bed, calling/texting, woke up, driving, other
Hour of day	-	Inferred from time
Day of week	-	Inferred from time

Fig. 1. Smartwatch data collection app while collecting sensing data. Application detects and marks data as off-body whenever wearable is not worn, and alerts user via color-coded UI.



(1) EMA push notification (2) Report current stress level (3) Report current situational context

Fig. 2. EMA / self-report data collection application on Android receiving a push notification triggered by server, and asking user to input their stress levels and situational contexts.

runs in background mode. Ensuring a high temporal coverage with least possible amounts of missing data is crucial for daily life stress sensing study. Hence, after thorough evaluations and testing we concluded that our smartwatch data collection application is reliable in real-life conditions when disabling Doze mode, adding application to WearOS whitelist using adb tool, and disabling Automatic workout detection features. We make our software available online[1].

We also implemented an Android application to deliver push notifications and collect EMA data using Firebase SDK. To ensure high user engagement, we paid special attention to making the User Interface user friendly, and interactive. The application has two components, namely (1) dashboard that displays EMA submission statistics to the user (i.e., number of missed prompts, and submitted prompts), and (2) EMA submission screen with compact list of questions and options.

Finally, our centralized data collection server is implemented using Django REST framework, that is commonly used for development of robust API services. We followed test-driven development with consistent $\geq 90\%$ unit test coverage to avoid any errors in client the side (that could put Data Quality at risk) due to server-side crashes.

C. Future Study

We expect that extending the range and richness of the captured contextual information can shed light on the complex daily-life stress scenarios. Such information, as opposed to "high-level" context information [3], can help defining the user's rich situational contexts. We envision that this study will lead to the development of more reliable models for detecting stress in the wild.

[1] https://github.com/qobiljon/stress-wearos

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