Multimodal Data Collection Framework for Mental Stress Monitoring

Saewon Kye
Junhyung Moon
Juneil Lee
Inho Choi
Dongmi Cheon
Kyoungwoo Lee
Department of Computer Science
Yonsei University
Seoul, Republic of Korea
(saewon.kye; jh.moon.cs; juneil.lee; inho.choi; dmcheon; kyoungwoo.lee) @yonsei.ac.kr

UbiComp/ISWC'17 Adjunct, September 11 – 16, 2017, Maui, HI, USA.
 ISBN 978-1-4503-5190-4/17/09 $15.00
https://doi.org/10.1145/3123024.3125616

Abstract
Accurate recognition of people's responses to stress and timely management of stress is one of the important aspects of maintaining good health. However, recognizing such reactions is difficult since people react to stressful events in various ways. Accordingly, we propose a multimodal stress monitoring framework to examine people's physiological and behavioral reactions to stressors. Our framework consists of (i) multimodal data collection related to mental stress, (ii) stress inducing experiment in a laboratory, and (iii) signal examination software in real-time and after the data collection. Through preliminary experiments, we have examined how people show various reactions to different kinds of stressful tasks. Finally, based on the proposed framework, we will establish a database contributing to the mental health sensing research.

Author Keywords
Stress recognition; Wearable devices; Physiological signal monitoring; Activity monitoring

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous; J.3 [Computer Applications]: Life and medical Science - Consumer Health

Introduction

One of the key aspects in maintaining good health is through managing mental stress. Continuous exposure to stress can cause various health problems, such as depression, cardiovascular disease, etc [12]. Recognizing when people are getting stressed and properly relieving them can be an effective method to maintain good health (reference required).

In efforts to monitor people's mental health, various approaches have examined people's physiological and behavioral responses to stressful events [4, 6, 13, 5, 8, 3, 10]. However, since these studies rely on one or two wearable devices, the proposed systems are not able to examine people's physiological and behavioral responses to stressors at the same time. People may show various kinds of responses to the same stressors and the same person may react in different way during different stressful environments. For example, when people are presenting in front of a large crowd, some might sweat while others might shake their hands. Further, a person might breathe irregularly when he or she meets someone for the first time whereas the person might breathe increasingly fast during a presentation. Accordingly, people experiencing stressful events should be examined in multiple perspectives using various sensors.

Accordingly, we propose a multimodal framework for monitoring people during stressful events. Our framework collects people's physiological and motion sensor data. In the framework, three commercial wearable devices, Empatica E4, Zephyr Bioharness Module, and LG Watch Style, and a IP (Internet Protocol) camera collect 8 different types of sensor data at the same time. As for the data collection related to stress, we have utilized popular stressors in existing research to induce stress to participants [1, 11, 7]. In addition, we also have developed a program, which monitors sensor data collected during the experiments. The program receives various signals from the wearable devices, checks the connectivity between wearable devices and the server, and visualizes the collected data comprehensibly. Based on the proposed framework, we plan on constructing a public on-line database which broadens the understanding of mental stress and further contribute to the affective computing and mental health sensing communities.

Related Works on Stress Recognition

Existing research have used various wearable devices to estimate mental stress in several contexts. Typically used physiological sensors embedded in wearable devices are EDA (electro-dermal activity), PPG (photoplethysmogram), ECG (electrocardiogram), and Resp (respiration); which measure skin conductance, heart rate, heart activity, and breathing rate, respectively. In addition, motion sensors from wearable devices, image, and audio sensors examine people's behavioral features, such as movements, facial expressions, voice and so on.

To continuously and unobtrusively monitor such signals, existing research have utilized various wearable devices. Table 1 compares the state-of-the-art studies on stress monitoring against the proposed framework. Those research have appropriately captured whether people were stressed or not, but can be insufficient to cover various responses against stress. For example, [3, 8, 9] are not able to monitor people's behavioral responses during experiment, such as shaking one's hands, since accelerometer and gyroscope are excluded in the framework. Further, [4] fails to monitor people who show little facial expression and have no habitual movements under stressful episodes. In [6], movement data are just used to remove noisy information and they fail to capture behavioral features caused by stressors.

Figure 1: The wearable devices used in the proposed framework should minimize discomfort and restriction on a person's movement

Table 1: Under the proposed framework, people's physiological and behavioral reaction can be comprehensively examined

Reference	EDA	PPG	ECG	Acc (wrist)	Acc (chest)	Resp	Image	Audio
Proposed method	✓	✓	✓	✓	✓	✓	✓	✓
Mozos, 2017 [10]	✓	✓			✓			
Chan, 2016 [3]			✓					✓
Koo, 2016 [8]	✓							
Gjoreski, 2016 [5]	✓	✓		✓				
Wu, 2015 [13]			✓		✓			
Hovsepian, 2015 [6]			✓		✓	✓		
Gao, 2014 [4]							✓	

[10] does not investigate changes in heart activity under by stressful incidents and further, [13] lacks in considering the skin conductivity of people.

To properly examine various responses of people under stressful environment, we have develop a multimodal data collection framework which consists of 8 different sensors widely used in stress recognition research as described in Table 1. The data from the experiment will be used to analyze people's various kinds of reaction to stress and will be further used to develop a stress recognition model which will reflect individual characteristics.

Comprehensive Data Collection Framework

Data collection method

In the proposed framework, the Empatica E4 Wristband, LG Watch Style, Zephyr Bioharness Module, and the IP (Internet Protocol) camera examine people's reactions to stressors during the stress inducing experiment. The three wearable devices can be easily and comfortably worn, and is embedded with the sensors used in existing stress recognition research. Table 2 describes the sensors in each device and body parts to be worn on. Figure 1 shows one participant wearing all devices. The location of each device are chosen so that the data from each sensor can be accurately acquired and can be comfortably worn by a person. Also, the IP camera is installed at a corner of the experimental room to record the test participant at a distance.

The Empatica E4 Wristband is worn on non-dominant hand to monitor skin conductance, heart rate, and movement of the hand. One of the advantages of Empatica E4 is that EDA signals are measured from the wrist rather than fingers. Typically, other wearable devices measure skin conductance from fingers which limits one's activity while wearing the sensors. To minimize the discomfort in wearing the device, we utilize Empatica E4 Wristband of watch-type band. Further, LG Watch Style is a state-of-the-art smartwatch embedded with accelerometer and gyroscope. Since smartwatches are widely used in everyday life, we hypothesize that it is one of natural ways to monitor a person's hand movement in both labs and during daily life. As for the placement of each device, since physiological signals may contain noise data if there are movements during data acquisition, we have decided to wear the Empatica E4 on non-dominant hand. LG Watch Style is only embedded with motion sensors. Accordingly, the smartwatch is worn on the dominant hand where the test participants will make more movements compared to that of non-dominant hand.

Table 2: Devices can be comfortably worn and are embedded with sensors used in existing stress recognition research

Device	Sensor	Features	Location
Empatica E4	EDA PPG Accelerometer Temperature sensor	Skin conductance Heart rate Movement Body Temperature	Non-dominant hand
LG Watch Style	3-axis Accelerometer 3-axis Gyroscope	Directional movement of hand Rotation angle of hand	Dominant hand
Zephyr Bioharness	Respiration sensor ECG Temperature sensor 3-axis Accelerometer	Respiration rate Heart rate variability Body Temperature Posture	Around chest
IP Camera	Image sensor Audio sensor	Video of experiment Voice and noise	Facing participant

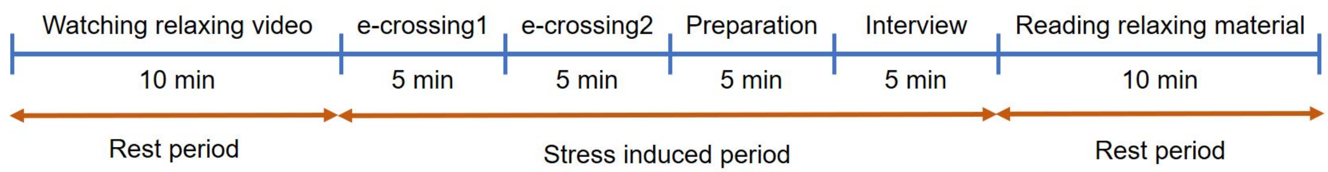


Figure 2: During the experiment, each test participant will go through 20 minutes of relaxation period and 20 minutes of stress induced period.

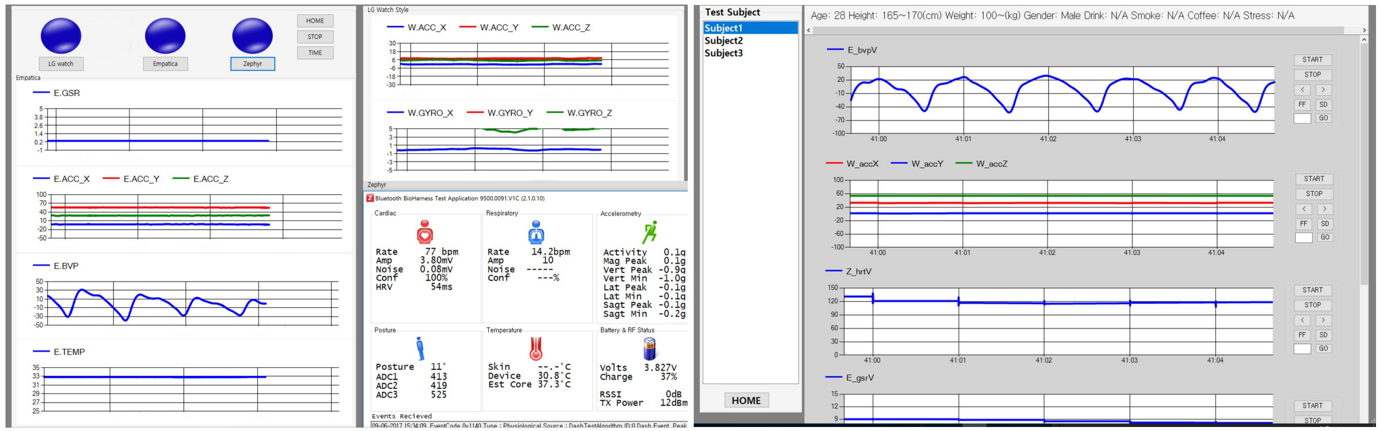
Zephyr Bioharness Module is a chest-worn device close to the heart. The device is widely used for monitoring heart activity of athletes during training and in games. Because the device can accurately measure physiological signals in the presence of violent movements, we have hypothesized that the device can also be used in people's ordinary day. Additionally, an IP camera is installed in the experimental room to monitor participants at a distance. This captures not only several physical movements and facial expressions but also voice. We aim to acquire meaningful data for estimating stress.

Experimental scenario

To understand how people react against stressful episodes, we have designed a laboratory experiment based on the protocols used in (references). Our experimental scenario consists of setup, rest, stress inducted, recovery, and debriefing stages. In the setup stage, participants will be given instructions on the tasks that they will be performing and how to wear the devices. To remove any potential bias that can be caused from prior knowledge, we disclose the real purpose of the experiment at the debriefing stage. During the debriefing stage, they will be told the goal of the experiment and detach the devices. As for inducing stress to people, the experiment participants of the conventional works have performed utilized cognitive and socio-evaluative works. Since it has been demonstrated that they are successful in inducing stress [1, 11], we base the design of our experiment on such tasks. Figure 2 shows the experimental timeline for one participant excluding the setup and the debriefing phases.

After the setup phase, the data collection from three wearable devices and the IP camera will start and the participants will move on to the rest period to neutralize their emotions before stress induction. In the rest period, the participants will be watching a relaxing video for 10 minutes. The video is a clip showing natural environment, such as flying birds or a lake, with slow-tempered relaxing music.

For the first stressor of our experiment, we utilize "e-crossing" [7] where the participants exercise a cognitive task. In this period, the participants are given a piece of paper filled with texts and are instructed to cross out as many "e"'s as possible. This task lasts for 5 minutes and we call this sub-period as "e-crossing1". After "e-crossing1" is finished, the participants are given another piece of paper with different texts and they would conduct a similar task. In this section, they are instructed not to cross out "e" if there are three or more "e"'s in one word. For example, the participants should not cross out "e"'s in the word "between" since three "e"'s are in this word. This period is called "e-crossing2" and lasts for 5 minutes. According to [7], people enter the stage of ego-depletion during the tasks and eventually receive stress by



(a) The incoming data from all three wearable devices can be monitored in real-time

(b) The form visualizes the database and each graph can be manipulated in various ways

Figure 3: The program is a centralized data collection software where the devices' connectivity, incoming data and the constructed database can be viewed

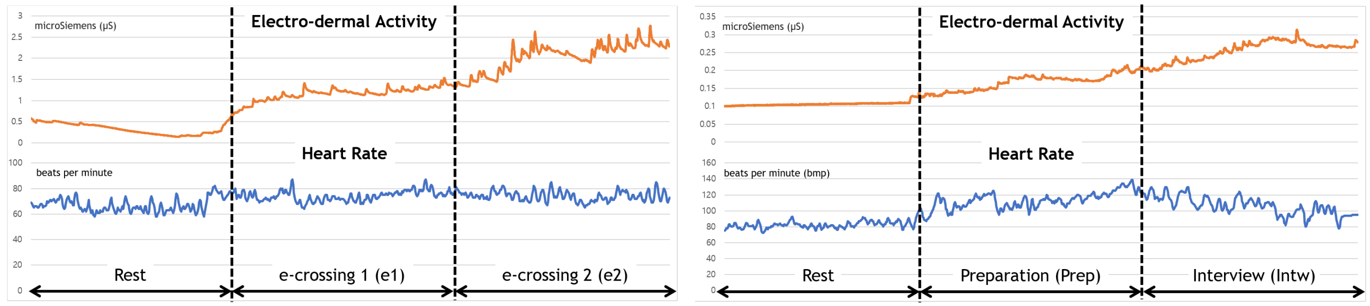
performing such cognitive task.

After finishing the "e-crossing", the participant is involved in a socio-evaluative task, an interview. An interview has been widely utilized for inducing stress [1, 11]. Moreover, the participants are forced to speak in a non-native language to induce even more stress. For the first part of this stage, which we refer as "Preparation" stage, the participants are given a piece of paper with the interview questions and prepare the answers for 5 minutes. After 5 minutes, a native speaker will come into a room and will conduct the interview for 5 minutes. The interviewer will ask previously handed out questions and some follow up questions until the given time is over.

Once the whole stress induction periods of "e-crossing" and the interview are finished, the participants are given a material to read for 10 minutes to recover from the stress. During this period, which we refer as "Recovery", the participants will be given a magazine which contains emotion neutral contents. Once this period is over, we stop collecting the sensor data as well.

Data Examination Tool

To easily check the connection status between wearable devices and a host device, and to intuitively examine incoming signals, we have developed a C# application. The application running on the host device (i) starts a connection with each device and receives data, (ii) monitors the incoming data in real time, and (iii) organizes the data into a database and visualizes them. Figure 3 presents main pages of our application utilized in the experiments.



(a) "e-crossing" experiment increases participant's overall EDA and heart rate

(b) During the interview experiment, the overall tension that the participant receives increases

Figure 4: The participant's physiological signals change while performing the proposed stress inducing tasks

Figure 3a shows the form in which the three wearable devices can be connected to the server and connectivity of the devices during the experiment can be monitored. A user can connect to each device and starts data collection in the top left corner of the screen. Empatica E4 and Bioharness module communicate with the server using Bluetooth. As for the LG Watch style, the device communicates data over TCP (Transmission Control Protocol) wireless. Once each device is successful in connecting to the server, the color of the corresponding device's circle will change to blue. As soon as the host device starts to receive the data, the program plots the data on the graph and saves the data to csv file simultaneously. As for the Bioharness module, since the manufacturer provides limited access to their API for developers, we utilize the sample bluetooth communication software provided by the company. The program monitors if the device is correctly acquiring signal and the sensor data are saved within the device. The collected data is later exported to the server.

Each sensor data is saved at a separate csv file. Later, the collected data are organized into the database and are later visualized in Figure 3b. On the box located at the left of the form, there shows the list of the participants where each participant is identified as an unique subject number. When each subject number is clicked, the collected data are shown in the form. The personal information is shown on the box located at the top of the form. Note that these data represents statistical information only for the research purposes and cannot be utilized to break one's privacy. Each sensor data is visualized in a graph. Once the start button is pressed, the graph shows how the sensor data changes according to time. The speed in which the program displays the data can be manipulated. Further, the program can be fast-forwarded or reversed to any given time chosen by the program user.

Preliminary Experiment Result

To examine the feasibility of the proposed framework and effectiveness of the proposed stressors, we have conducted preliminary experiments. Four people participated in the experiment and they went through the rest period and either

(bpm)	AVG	MAX	MIN
Rest	67	82	58
e1	74	87	64
e2	73	85	65
Rest	81	93	64
Prep	110	134	76
Intw	107	139	78

Table 3: The participant's heart rate were higher during the stress inducing tasks compared to that of during rest period.

"e-crossing" period or interview period while wearing all three devices.

Figure 4 displays the graphs of EDA values measured from Empatica E4 and the heart rate calculated from Zephyr Bio-harness module. Figure 4a is the graph of the participant's change in physiological signals during "e-crossing" and the participant in Figure 4b went through interview. Through the preliminary experiments, we were able to examine the changes in physiological data during stress induction periods. In both scenarios, both of the particiapnts' EDA value and heart rate value during stressor activities were higher than those of during Rest period.

In addition to the increases in the values of EDA and heart rate, we were able to observe how people have various reactions to different types of stressors. Compared to the participant who performed the interview, the participant who performed "e-crossing" showed more abrupt increased in the EDA values. Such peaks are called as Skin Conductance Responses (SCRs) and such phasic EDA reactions often occur when people are exercising cognitive tasks, such as decision making or anticipation [2]. Even though both tasks increased the overall level of EDA values, more SCRs can be examined during "e-crossing" than during the interview since people more frequently involve in decision making during "e-crossing" than during an interview.

We have also examined how people's heart rates are influenced during each task. The average heart rate of both participants were higher during stress inducing period than that of rest period. Table 3 shows the average, the minimum and the maximum heart rate of each period for each experiment. During the stress induction period, the overall heart rate was higher than that of during rest period. However, the heart rate of participant in Figure 4a were relatively steady compared to that of the participant in Figure 4b. We hypothesize that the participant in Figure 4b were able to control this heart rate by controlling how he breathes while he was talking.

Conclusion

In this work, we have proposed the multimodal framework for collecting physiological and motion data of people under stress. Physiological, motion and multimedia sensors from three commercial wearable devices and an IP camera are used to monitor people's various reactions to stressors. We have also designed a stress inducing experiment where participants will exercise cognitive and socio-evaluative tasks. For the signal checking and data collection during the experiments, we have developed a C# program which monitors incoming sensor data in real-time and later visualizes the constructed database. Through the preliminary experiments, we were able to examine the effectiveness of the proposed stressors in inducing stress to the participants. During the stress induction period, the participants' physiological signals not only increased but also showed various characteristics in response to different kinds of stressors.

The proposed framework and the experimental setup have been approved by Yonsei University Institutional Review Board. As for the future work, based on the data collected from the experiments, we plan on building a stress estimation model. In particular, we expect to build not only a personalized model but also the universal model where the model can be applied to various types of people. As for improving our framework, we further plan on investigating the effective location to wear each sensor. For example, EDA can also be measured from a person's ankle [14]. Each sensing location will be evaluated in terms of accuracy, effectiveness in estimating stress and comfortability in wearing the sensor in various contexts. Finally, the constructed database and the software will be open-sourced to contribute to the mental health sensing community.

Acknowledgements
This work was supported by Institute for Information & Communications Technology Promotion(IITP) grant funded by the Korea government(MSIP) (R0124-16-0002, Emotional Intelligence Technology to Infer Human Emotion and Carry on Dialogue Accordingly).

REFERENCES

1. Mustafa et al. Al'Absi. 1997. Cardiovascular and neuroendocrine adjustment to public speaking and mental arithmetic stressors. *Psychophysiology* (1997).
2. Hugo D et al. Critchley. 2000. Neural activity relating to generation and representation of galvanic skin conductance responses: a functional magnetic resonance imaging study. *Journal of Neuroscience* (2000).
3. Chanwimalueang Theerasak et al. 2016a. Modelling stress in public speaking: Evolution of stress levels during conference presentations. In *Acoustics, Speech and Signal Processing (ICASSP)*. IEEE.
4. Gao Hua et al. 2014. Detecting emotional stress from facial expressions for driving safety. In *Image Processing (ICIP)*. IEEE.
5. Gjoreski Martin et al. 2016b. Continuous stress detection using a wrist device: in laboratory and real life. In *ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*. ACM.
6. Hovsepian Karen et al. 2015a. cStress: towards a gold standard for continuous stress assessment in the mobile environment. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*. ACM.
7. Job Veronika et al. 2010. Ego depletion - Is it all in your head? Implicit theories about willpower affect self-regulation. *Psychological science* (2010).
8. Koo Helen et al. 2016c. Stresssense: skin conductivity monitoring garment with a mobile app. In *Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*. ACM.
9. Lyu Yongqiang et al. 2015b. Measuring photoplethysmogram-based stress-induced vascular response index to assess cognitive load and stress. In *ACM Conference on Human Factors in Computing Systems*. ACM.
10. Mozos Oscar Martinez et al. 2017. Stress detection using wearable physiological and sociometric sensors. *International Journal of Neural Systems* (2017).
11. Plarre Kurt et al. 2011. Continuous inference of psychological stress from sensory measurements collected in the natural environment. In *Information Processing in Sensor Networks (IPSN)*. IEEE.
12. Segerstrom Suzanne C et al. 2004. Psychological stress and the human immune system: a meta-analytic study of 30 years of inquiry. *Psychological bulletin* (2004).
13. Wu Min et al. 2015c. Modeling perceived stress via HRV and accelerometer sensor streams. In *Engineering in Medicine and Biology Society (EMBC)*. IEEE.
14. Richard Ribón et al. Fletcher. 2011. Wearable sensor platform and mobile application for use in cognitive behavioral therapy for drug addiction and PTSD. In *Engineering in Medicine and Biology Society, EMBC*. IEEE.