Year 9

Final Project Report

2020-2021

Center for Visual & Decision Informatics

Project 9a.008.UL - Privacy-aware stress & activity prediction using multi-modal sensing: Application to smart hospitals

A National Science Foundation

University Cooperative Research Center

Contents

Personnel

- Raju Gottumukkala – PI
- Christoph Borst – Co-PI
- Ziad Ashkar – Co-PI
- Satya Katragadda – Co-PI

Executive Summary/Abstract

Automated methods to detect human behavior enables the intelligent systems to better adapt to human behavior. Recognizing human activity and emotion in buildings is import for various reasons such as assessment of employee well being, energy and space optimization, etc. Many organizations such as hospitals analyze stress using survey based methods. But these methods are cumbersome, and are subject to recall bais, noise and uncertainity. The primary goal of this project is to improve the performance of stress detection methods with wearables in real-world conditions. Studying stress "in the wild" in a work environment is complex due to the confluence of many social, cultural, and individual factors in dealing with stressful conditions. The project is an extension of previous years work on stress detection. We designed a study to compare the performance of stress detection with wearables and a traditional survey for nurses in a major hospital. We leveraged real-time stress detection methods and tools developed from prior work. The project's key outcomes are improved stress detection models, a human subject stress study on nurses in a major hospital, a novel stress detection data-set, and detection of basic activities of nurses from accelerometer sensors.

Goals and Objectives

- Provide an agent that is consisted of data collection wearables, machine learning architecture, and an everyday survey platform to improve stress detection.
- Investigate privacy-preserving methods on Spatio-temporal data from the presence and biofeedback sensing
- Provide activity recognition data-set using only a wristband.

Differences from Current State of Art

- Existing stress detection methods use more than one wearable to detect stress and the stress detection data-sets are in controlled laboratory conditions. However, our model uses only a wristband with minimum intrusion for the subject during their daily work.
- Investigation of between-subject stress detection is challenging due to personalized stress detection methods. In this study, we investigated the between-subject stress detection to improve
- It provides an "in-the-wild" data-set that contains more than 1200 hours worth of data for stress detection of the nurses. This study has been done in the COVID-19 pandemic and can be a valuable data-set to investigate the pandemic effect on the nurses' stress in the hospital.
- The activity data-set is collected more than 12 hours of ten participants performing different activities, namely computer work, sitting, walking, running, ascending, and descending stairs. This data set used only a wristband to detect different activities, and it showed promising results in terms of accuracy.

Figure 1 presents the framework for the data collection apparatus.

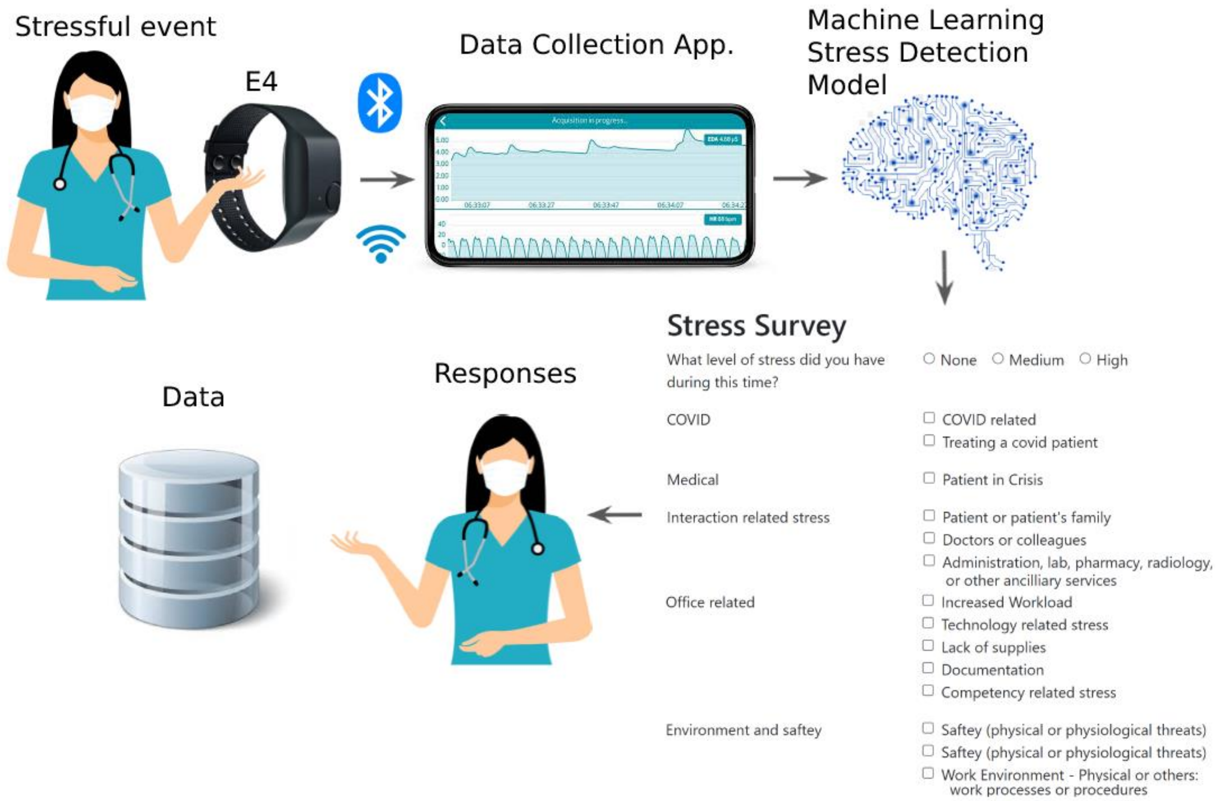


Figure 1 Description of Stress Detection Apparatus

The data was gathered for approximately one week from 15 female nurses working regular shifts at a hospital. The age of the nurses ranged from 30 to 55 years. In total, 1,252 hours worth of data was collected in two study sessions in Apr-May and Nov-Dec of 2020. In addition, 137.23 hours of data were detected as stressful. Picture

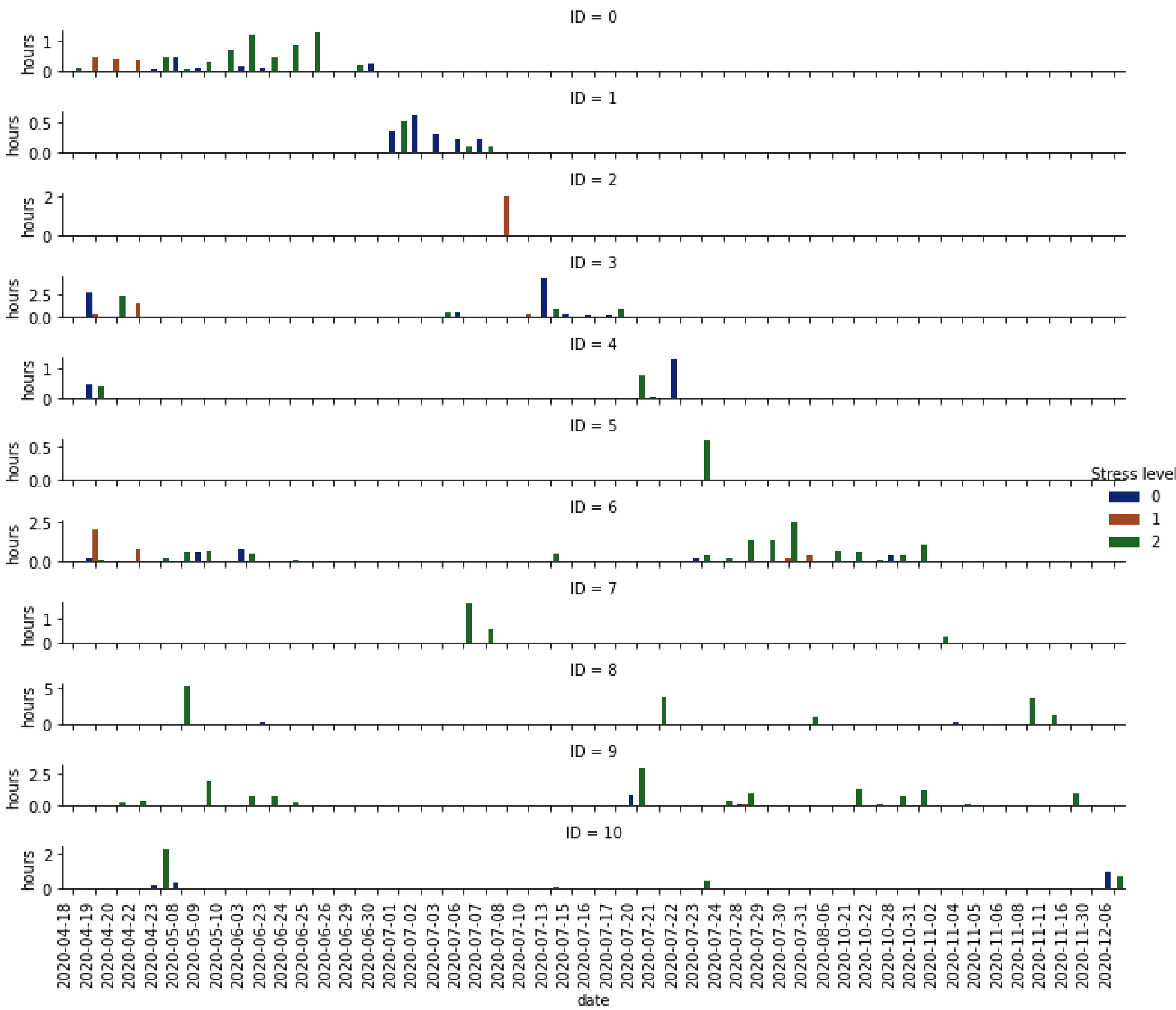


Figure 2 Stress Levels of various subjects during the study period

This ongoing work is further extended from using Empaica E4 as a unimodal stress detection device to using a combination of E4 signals and video for multi-modal representation learning. The uni-modal signals included stress detection data-set for the nurses. Fifteen nurses participated in the study. We collected more than 1200 hours of data from nurses and asked them only to validate stressful events to ensure the minimum intrusion during their work. A survey study had the responsibility of providing the context and data validation.

During these experiments, we collected the physiological data from the nurses continuously from the start of their shift to the end of the shift. We detected stress events while monitoring the biometric signal streams of nurses. The nurses were then asked to validate the detected events with a survey response. The data set is anonymized and will be made available upon request.

Stress inducers and context:

The questions in the questionnaire were selected based on a review of literature studying stress on nurses in hospital environment, as well as from our discussions with nurses. A list of questions in the survey is presented in table-1

Table 1 Factors affecting stress

COVID	COVID related [CR] Treating a COVID patient [TCP]
Medical	Patient in crisis [PiC]
Interaction related stress	Patient or patient's family [PoPF] Doctors or colleagues [DoC] Administration, lab, pharmacy, radiology, or other ancillary services [Ad]
Office-related stress	Increased Workload [IWL] Technology related stress [TR] Lack of supplies [LoS] Documentation [Doc] Competency related stress [CRS]
Environment and safety	Safety (physical or physiological threats) [Saf] Work Environment - Physical or others: work processes or procedures [WE]

Results

This project studied nurses' stress during the COVID-19 pandemic based on our findings on machine learning models for stress detection. The study was privacy-aware, and the participants were not monitored during the study. As a result, we got 80 percent accuracy while validating the stress of nurses in the data validation. The table shows the results of stress detection of nurses during this study.

Table 2 Summary of data and performance for each subjects

User id	Hours	# events	Duration	Accuracy
94	83:16	36	08:16	0.412
E4	120:13	38	19:06	0.818
7A	80:05	45	6:07	0.914
83	149:48	30	12:28	0.762
CE	111:02	17	8:00	1.000
15	70:05	31	7:07	0.769
8D	80:40	25	5:23	0.778
F5	58:00	8	15:31	0.667
5C	65:38	27	04:50	1.000
EG	115:18	12	13:39	0.900

6B	107:52	42	9:50	1.000
7E	58:07	23	6:26	0.846
8B	50:42	7	2:12	0.500
DF	26:29	16	15:33	0.800

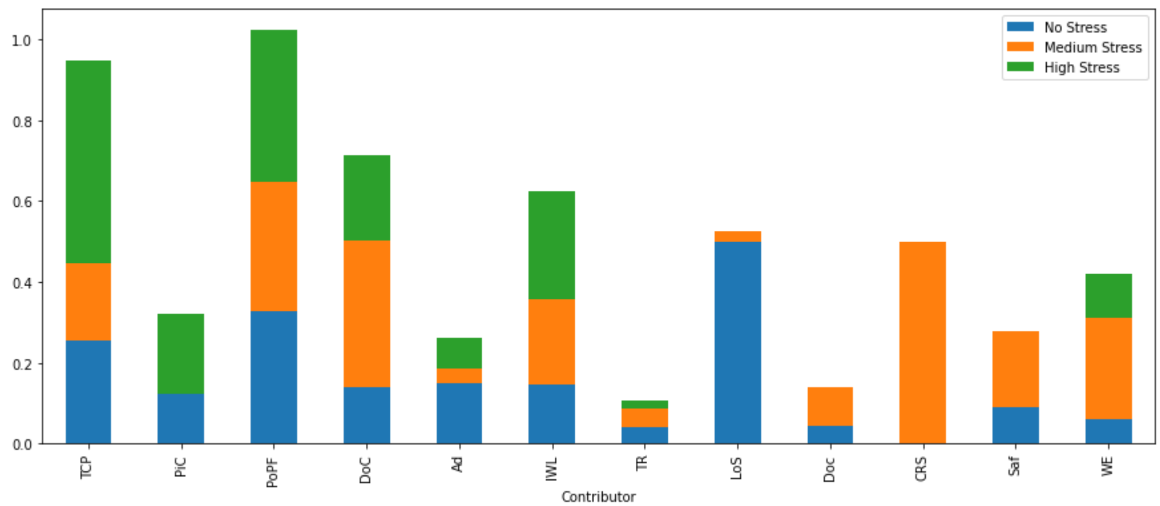


Figure 3 Performance of Stress Detection Methods for Different Factors

Figure 3 shows the stress contributors. In this study, treating a COVID-19 patient was reported as the most significant contributor to high stress. However, there was only one claim about COVID-19 or fear fromCOVID-19 itself. Lack of supplies was a significant problem in this period; however, it was not mentioned to contribute to acute stress.

We discuss different signal properties related to stress. First, the normal skin temperature for a person is about 33°C or 91°F. Skin temperature varies for various activities due to skin blood temperature and its flow and is generally within 33.5 to 36.913. However, this can vary quite widely based on the type and length of activity and indoor room temperature. Given the open-ended nature of the experiment, there are some anomalies in the data. Of 15 subjects, 11 subjects had higher skin temperature in high-stress events than medium-stress or low-stress situations. The relationship between skin temperature and stress has been discussed by Herborn et al [1]. Figure 4 shows the skin temperature of various participants.

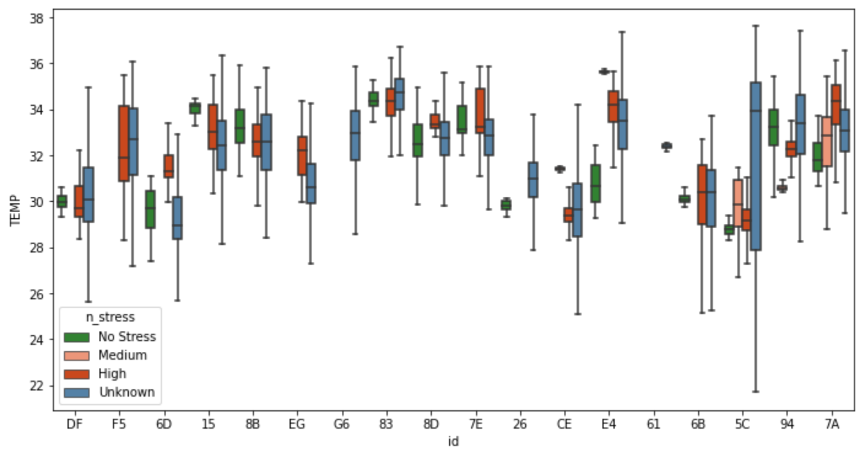


Figure 4 Heart rate of various subjects

The heart rate for a normal person, despite the sex, ranges from 60 to 100 while in a resting state. However, this changes due to different activities and the duration of the activity. Given that the subjects are doing different activities, one can observe high variation in heart rates. Figure 5 shows the distribution of heart rate and associated stress level for all the subjects. Stress did not have a strong correlation with the heart rate itself. However, there are lots of claims that heart rate variability is an essential signal in stress detection. Moreover, the average heart rate is higher in stressful situations for certain participants.

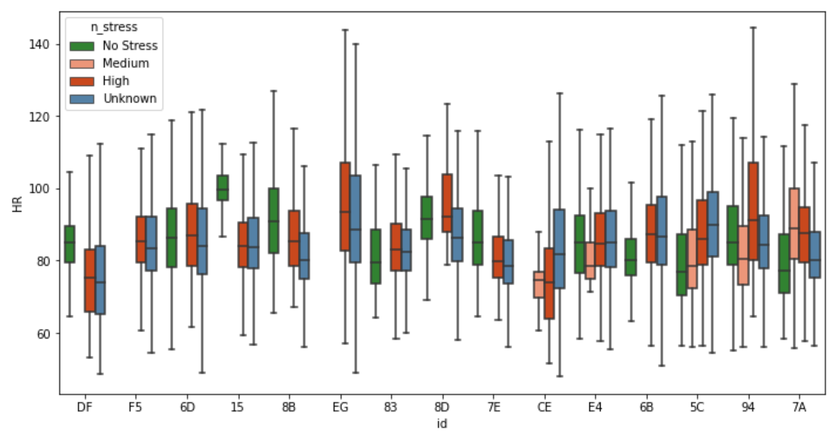


Figure 5 Heart rate of various subjects

Figure 6 shows the distribution of electrodermal activity and associated stress level for all the subjects. Stress has a strong positive correlation with the electrodermal activity for 10 out of 15 participants. Average of EDA is higher in stressful situations for some participants. However, for some participants, the EDA is not a good indicator of stress because EDA does not vary or it is not positively correlated. There is high variability in EDA signal for various subjects in stressful events. The normal range for humans is from 1to 20 microsiemens We observe that the average skin's electrodermal activity for all the participants whenthere is no stress reported is below 5, and the range for low stress is the same as stress free situations.However, EDA can go up to 60 in stressful situations based on the activity participants perform.

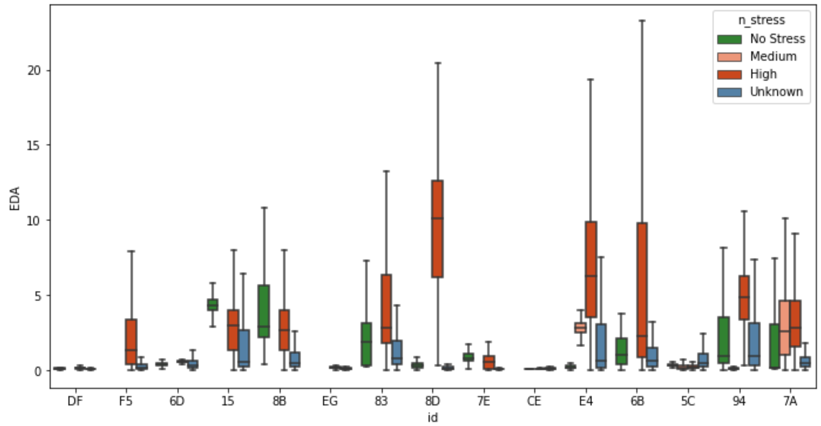


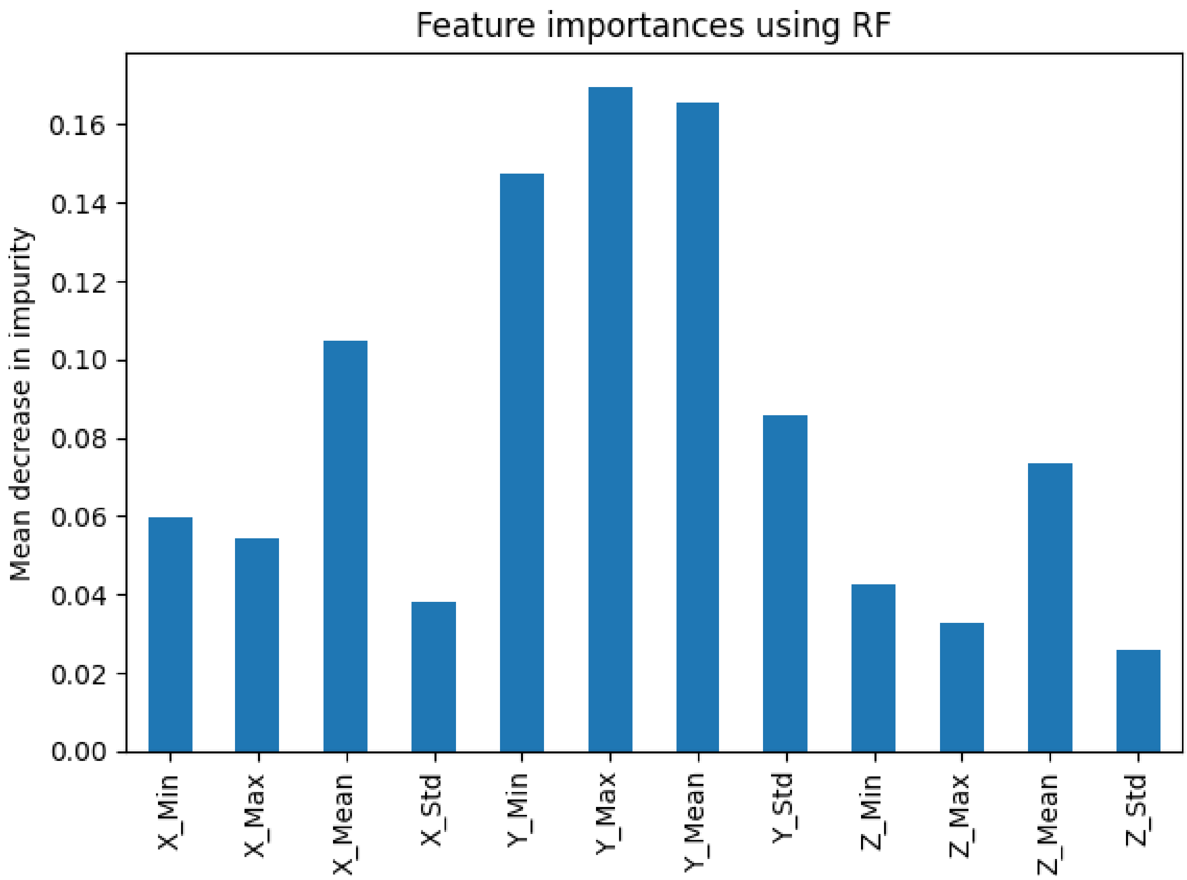
Figure 6 EDA of various subjects

The activity data set consists of 7 different activities. The table shows the activities and their durations.

No:	**Activity**	**Duration (min)**
1.	Computer work	250
2.	Sitting	223
3.	Walking	187
4.	Lie Down	33
5.	Running	25
6.	Ascending Stairs	15
7.	Descending Stairs	10

We also provided a machine learning model to recognize activity using accelerometer data and time-domain features, and we got 90 percent accuracy using only wristband data.

Table 4 shows the statistical features and their importance in the activity recognition model.



We also used the average of different axis accelerometer data and minimum and maximum of y_axis accelerometer for activity recognition.

The above study is currently being extended to include multi-modal stress detection (that includes using a combination of video, stress signals from Empatica E4 and indoor positioning information)

Functionality of Innovation(s)

The proposed stress detection apparatus can detect stress with minimum intrusion in the real-world environment. Furthermore, the survey labels and context were collected at the end of each working day to ensure the accuracy of answers, hence preserving the intrusion and privacy concerns. The framework was enabled to tune the stress based on the participants' feedbacks to the surveys.

Conclusions and Recommendations

Through this project (which was an extension from prior year project), we collected more than 1200 hours worth of stress data of nurses from Opelousas General Hospital in Louisiana. We preserved the privacy of the nurses during the data collection by only collecting their anonymized biometric signals with minimum intrusion. As a pre-requisite of a new project, we have the stress detection module and surveys. And we started a new collaborative work with Tampere university in multi-modal stress and emotion recognition using video and Biometric feedback. The Ethical review and IRB documents for both universities got approved, and we started a new set of data collection.

Impact and Uses/Benefits

We believe this study can be helpful for researchers in many domains. First, this data set is useful for researchers to improve the stress detection performance of the models. Second, we provided accelerometer data and the stress that helps detect activities to understand the relationship between activity and stress. Finally, we provided the stress survey results in stressful events that help the researchers in several eras, e.g., human resources, human factors, and organizational psychology, to associate between biometric signals and stress-related factors during the COVID-19 outbreak. Even without the signal data, the data-set would be additionally valuable to understand the differential distribution of various work-related stressors during the pandemic.

Moreover, the ongoing study on multi-modal representation fuses different signals to improve stress and emotion detection algorithms. In this study we started a new study and data collection to find the relation between stress and facial features.

List of References

Herborn, K. A.et al.Skin temperature reveals the intensity of acute stress. Physiol. & behavior152,225–230 (2015).