9^{th} International Conference on Computational Social Science IC^2S^2
July 17-20, 2023, Copenhagen, Denmark

The Stress of Daily Life: Towards Automatic Stress Detection

Keywords: stress detection, models of human behavior, social stress

Abstract

Daily pressure, work load, and family responsibilities among other factors impose increasing levels of stress on different individuals. Detecting stress as early as possible can potentially reduce the consequences and risks that individuals may experience. Additionally, the automatic detection of stress can help uncover insights into activities and social situations associated with stress. In this paper, we present a dataset of recordings of high- and low-stress for 50 subjects. We analyze different physiological features and present a system that integrates these features with results exceeding 75% accuracy, which can provide a useful and reliable approach for the detection of stress.

Introduction

Stress is a major problem that can result in severe consequences [2, 3]. In a report from an annual study conducted by the American Psychological Association (APA) to identify and analyze various critical elements associated with stress, it was found that money, work, family responsibilities, and health concerns were the most significant stressors [4]. Apart from the fact that stress is known to be associated with serious chronic diseases, e.g., depression, diabetes, and hypertension, either due to a defined pathological mechanism or due to other factors (e.g., genetic factors) that patients may have, stress can pave the way for healthy patients to acquire such diseases through driving them to follow unhealthy behaviors to cope with their problems. For instance, among 42% of the 3,068 study participants resorted to staying awake at night, and 33% adopted poor eating habits (e.g., overeating or consuming unhealthy food) to relief their stress. Adults from age 18-35 were found to be the most stressed group among all the other age groups. Interestingly, women (49%) were found to be more stressed than men (38%) in particular due to monetary responsibilities.

In this paper we present a multimodal dataset of recordings of people experiencing high and low stress, and describe a system that can detect the presence of stress with over 75% accuracy. We believe such stress detection systems can be used to estimate the stress level associated with daily social [6, 1] and work activities [5], and thus gain insights into these stress-inducing activities, and can further help us reduce or avoid stress in daily life.

Stress Dataset

Subjects. Our dataset consists of recordings collected from 50 undergraduate and graduate volunteering students from the University of Anonymous. The subjects include 35 females and 15 males. All participants expressed themselves in English, belonged to several ethnic backgrounds, and had an age range between 20 and 35 years. The subjects were asked to sit comfortably in the experiments station and were informed that they were participating in a behavior study, without explicit indication regarding stress detection.

Materials. Three scenarios were designed for the experiments, where the subjects had to present in a persuasive manner arguments that are either truthful or deceptive. These scenarios were selected based on previous work that found that making persuasive arguments and being deceptive can induce stress. In two scenarios, namely, "Abortion" and "Best Friend," subjects were allowed to speak freely about their true opinion on the given topic and about the opposite view of their true opinion, while in the third scenario "Mock Crime", the subjects had to respond to several questions asked by an interviewer. Additionally, before recording the three scenarios, the subjects were asked to relax and sit comfortably for a one-minute recording with no activity on their side; the same process was repeated at the end of recordings. We refer to these recordings as "Inactive 1" and "Inactive 2."

Recording Equipment. In order to collect our human-centric physiological data we used a thermal camera and four physiological sensors. In particular we used a top-of-the-line FLIR SC6700 thermal camera with a resolution of 640x512 and 7.2 M electrons capacity, reaching a frame rate of approximately 100 frames/second. We also employed four bio-sensors to collect physiological responses, namely blood volume pulse (BVP sensor), galvanic skin response (GSR sensor), and skin temperature (ST sensor), placed on the subject fingers; and abdominal respiration (BR sensor), placed around the thoracic region. Participants were instructed to avoid excessive movements in order to obtain high quality data.

Stress Self-Assessment. Each subject participated in seven recordings, resulting in a total of 350 responses. Once the recordings were finalized and the subjects were compensated, they were asked to self-assess the responses that were the most stressful and least stressful for them. This resulted in a total of 100 recordings evenly distributed between high-stress and low-stress, which are used as ground-truth in our experiments.

Models of Stress Detection

Starting with our dataset, we extract several physiological features, including statistical features compiled from the thermal map of various regions of the face; heart rate metrics; respiration rate metrics; skin conductance metrics; and skin temperature metrics.

Given the relatively small size of our dataset, we employ a decision tree classifier and a leave-one-subject-out cross validation scheme, where both the stress and non-stress instances of each subject are used for testing at each fold, whereas the instances of all other 49 subjects are used for training. This scheme is followed for a fair evaluation and to avoid any subject dependencies that might bias the results.

First, we evaluate the performance of each individual feature. We find that the features obtained by the thermal camera from the thermal map of the face lead to the best accuracy (72%), followed by skin temperature features (68%), skin conductance and heart rate (60%), and respiration rate (55%). We next evaluate combinations of features, and find that the best results are obtained by a model that combines respiration rate and thermal features (78%).

All these results are significantly higher than the baseline of 50%, which confirms that stress is indeed associated with variations in the participants' facial thermal maps and physiological characteristics, and these variations can be effectively leveraged for the automatic detection of stress. These results pave the way forward for new research directions to gain insights into daily activities and social situations associated with stress.

References

[1] Carol S Aneshensel. Social stress: Theory and research. *Annual review of sociology*, 18(1):15–38, 1992.

[2] J. Douglas Bremner and Eric Vermetten. Stress and development: Behavioral and biological consequences. *Development and psychopathology*, 13(3), 2001.

[3] Jeffrey R Edwards. The determinants and consequences of coping with stress. *Causes, coping and consequences of stress at work*, 8:233–263, 1988.

[4] American Association of Psychology. Stress in America: Paying with our health. https://www.apa.org/news/press/releases/stress/2014/stress-report.pdf, 2015.

[5] Jungwee Park. *Work stress and job performance*. Statistics Canada Ottawa, ON, Canada, 2007.

[6] Leonard I Pearlin. The sociological study of stress. *Journal of health and social behavior*, pages 241–256, 1989.