Affective Keys: Towards Unobtrusive Stress Sensing of Smartphone Users

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Abstract

This work explores the use of pressure-sensing to capture cues of the stress of smartphone users while typing. In a controlled laboratory study, 11 participants were asked to write about a recent stressful and relaxing experience in counterbalanced order. Preliminary results show a significant positive correlation between the increase in typing pressure and self-reported stress across the two conditions ($r=0.75$, $p=0.0081$). In addition, we observed a significant negative correlation between the typing pressure baseline and the self-reported stress ($r=-0.74$, $p=0.0093$). These findings can help inform the development of less invasive methods for stress measurement.

Author Keywords

Stress measurement; Pressure-sensitive keyboard; 3D Touch; Affective computing.

ACM Classification Keywords

H.5.2. Information interfaces and presentation: User Interfaces

Introduction

The average adult smartphone user interacts with the device more than 100 times a day [1][2]. Most of these interactions involve typing with the keyboard – to

search, to message someone, to post on social media, and so on [3]. Monitoring these interactions offers a unique opportunity to evaluate the possibility of passively sensing relevant information about the user such as her/his emotional state [4]. This work explores the possibility of using smartphone interactions in the context of stress. In particular, we focus on the stress associated with re-experiencing a stressful past memory. In contrast to other standardized stressors (e.g., arithmetic tasks, public presentations), this type of stressor is more subjective and occurs more frequently while communicating over the phone. By detecting early indicators of stress, we hope to inform the design of novel stress reduction interventions (e.g., [5]) that help reduce some of the adverse health conditions associated with chronic stress [6].

The paper is organized as follows. First, we describe relevant work considering stress sensing and keyboard behavior. Second, we describe the study design and the methods. Third, we review some of the main findings. Finally, we provide some discussion and concluding remarks.

Related Work

Stress is regularly described as an evolutionary response that helps us face life-threatening situations [7], but it often occurs in non-life-threatening everyday activities. While there exist several methods to monitor stress and other emotional states, they usually require expensive and invasive analysis (e.g., hormone testing), wearing of additional devices (e.g., physiological devices), or demanding the cognitive attention of users (e.g., self-reports). To help minimize some of these challenges, less invasive methods such

as monitoring typing behavior have been explored (e.g., [8], [9], [10]). For instance, Lv et al. [8] used pressure sensors on keyboards to recognize several emotions. While they obtained a classification accuracy of 93.4% for 6 different emotions, they did not consider stress. In a separate study, Epp et al. [11] showed the feasibility of detecting up to 15 emotional states with an accuracy between 77% to 88%. Nevertheless, their study focused on the analysis of typing patterns instead of typing pressure. In a more recent study, Hernandez et al. [12] used a computer keyboard and a mouse to monitor early cues of stress. Among other findings, their study showed that the stress associated with re-experiencing a stressful memory significantly increased keystroke pressure. However, this and previous studies have mostly considered stationary desktop conditions which may provide more limited sensing opportunities (e.g., only in the office) and may pose less challenges that mobile real-life scenarios (e.g., different types of body posture and activities, several phone handling behaviors). There are, however, some recent efforts that consider emotion recognition in other mobile settings [13][14][15]. For instance, Gao et al. [15] conducted a study to identify user emotions from touch interactions while playing a video game. Among other findings, their study showed that the number of pixels activated on the screen strongly discriminated frustration from other emotional states. However, no direct measurement of pressure was provided. Motivated by these studies, this work focuses on stress measurement of smartphone users while typing recent life experiences. To the best of our knowledge, we believe our work is the first to use pressure sensing in this context.

Figure 1: Custom QWERTY keyboard built for the study.

How are you feeling?

Choose from 1 to 7

Very unpleasant (negative)				Very pleasant (positive)		
1	2	3	4	5	6	7

Low Energy (calm, low arousal)				Very energetic (awake, high arousal)		
1	2	3	4	5	6	7

Not stressed at all				Very stressed		
1	2	3	4	5	6	7

Figure 2: Self-report survey for emotional valence, arousal, and stress levels on 7-point Likert scales.

Figure 3: Task orderings for different participants. Dashed blue and red rectangles correspond to relaxed and stressed conditions, respectively. EW: Expressive Writing.

Methodology

This section provides details about the input device, tasks, and data collection procedure.

Input device

To perform the data collection, we use the iPhone 6S Plus (Apple, Inc.) with iOS 11.1. One of the capabilities of this device is the 3D Touch, which provides pressure estimates for each touch interaction. This technology uses a combination of microscopic changes detected by the capacitive sensors and the accelerometer sensors of the device. The range of possible pressure values is 0 (no pressure) to a maximum pressure determined by the system (6.7 in our dataset). To collect the data, we built a custom QWERTY keyboard (see Figure 1) that logged the timing, position, and pressure values associated with each keyboard interaction.

Experimental Protocol

To study whether mobile typing pressure changes during stress, we designed a within-subject laboratory experiment in which participants performed an expressive writing task under relaxed and stress conditions in randomized order.

In particular, we requested participants to re-experience a relaxing and a stressful recent past memory and write about it for a recommended time of 5 minutes. To help avoid adding other sources of stress, participants had the possibility of submitting

their responses as soon as they felt they had written all that they could about the event. In addition, participants were allowed to make spelling, grammar, and sentence errors. Before each of the tasks, participants were requested to watch a short video of relaxing paradise beaches and/or to close their eyes for two minutes to help elicit a neutral state. After each of the tasks, participants were requested to self-report their emotional valence, arousal, and stress levels on a 7-point Likert scale (see Figure 2).

Participants of the study were instructed to sit on a chair, hold the phone with both hands, and use their thumbs for typing. To help minimize potential biases, they were told that the goal of the experiment was to better understand interactions with smartphones but were debriefed at the end of the experiment. They were also told the content of the writing was not collected due to privacy reasons. In addition, participants had to perform a short tutorial to help minimize the novelty effect of the device. In particular, they had to transcribe a short piece of text and complete a self-report survey. Figure 3 shows an overview of the whole experimental protocol. The total duration of the experiment was around 20 minutes and participants received a \$5 Amazon gift card compensation.

Data Overview

Twelve participants (6 females and 6 males) participated in this study. However, one of the male

Figure 4: Average self-reported ratings and their standard error for stress (top), valence (middle), and arousal (bottom) after the relaxed (blue) and stressed (red) conditions. *Wilcoxon signed rank test, $p < 0.03$

participants requested to end the experiment halfway through due to high-stress levels associated with his memory during the stressful EW. Thus, the data that was analyzed corresponds to $N=11$ participants (6 females and 5 males). The average number of keystrokes across participants was 593.64 (Standard Deviation=245.73) and 666.73 (STD=223.87) during the calm and stressed conditions, respectively. The average number of minutes was 3.79 (STD=1.31) and 4.18 (STD=0.94) during the calm and stressed conditions, respectively. All participants were fluent in English, had previous experience using smartphones (mainly iOS and Android devices), and did not suffer any tremors or have past history of upper extremity musculoskeletal disorders. These participants were recruited through e-mail sent to several mailing lists inside the academic institution. All participants except two of them had a background in computer science or related field. The average age for these 11 participants was 26 with a minimum of 19 and a maximum of 35 years old.

Results

Figure 4 shows the average self-reported ratings of emotional stress (top), valence (middle), and arousal (bottom) after the relaxed (blue) and stressed (red) conditions. Using the Wilcoxon signed rank test, we observe that the stressed condition was associated with significant increases in self-reported stress ($Z=2.588$, $p=0.010$) and arousal ($Z=2.232$, $p=0.026$), and a significant decrease of valence ($Z=-2.850$, $p=0.004$) which is consistent with the protocol expectations. When considering stress reports, these differences were consistent for 8 out of the 11 participants but the remaining 3 participants provided the same stress report for both conditions. Overall, these findings seem

Figure 5: Average typing pressure and self-reported stress in the relaxing (blue) and stressed (red) conditions for all the participants (dotted lines).

to support that the different tasks elicited the intended emotions for the majority of participants. However, clearer instructions and/or longer expressive writing tasks would be recommended to better elicit the intended emotions in all the participants.

Figure 5 shows the average typing pressure and self-reported stress in the relaxing (blue) and stressed (red) conditions for all the participants. Conditions belonging to the same participant are connected with a dotted-line. As can be seen, there are large individual differences both in terms of typing pressure and self-reports, which is to be expected due to the subjective

nature of stress. The three participants who provided unchanged stress self-reports can be easily identified by the straight lines along the vertical axis (i.e., P5, P7, P10). By contrast, two participants (i.e., P3, P6) show a relatively large variety on stress levels. We believe the differences between these previous two clusters are associated with the effectiveness of the stressor and how it varied across people. Overall, we can observe an increase for both stress self-reports and typing pressure for most of the participants after the stressed condition. To help assess the consistency of these changes, we computed the difference in typing pressure and self-reported stress for each of the participants and computed their Spearman's Rank-order correlation. As hypothesized, we found a significant positive correlation ($r=0.75$, $p=0.0081$) which indicates that an increase of self-reported stress is usually associated with an increase of typing pressure and vice versa. In addition to these differences, we can also observe that participants seem to cluster into two different groups: one with lower stress self-reports and higher typing pressure baseline (i.e., P2, P3, P5, P6, P8), and another one with higher stress self-reports and lower typing pressure baseline (i.e., P1, P4, P7, P9, P10, P11). These differences become even more apparent when only considering the values associated with the relaxed condition (due to large self-report increase of P6). Similarly, we use Spearman's correlation between the two variables and found a significant negative correlation ($r= -0.74$, $p=0.0093$) which indicates that participants with lower stress ratings may have higher typing pressure baselines and vice versa. These two clusters seem to be independent to the ordering of the conditions, the gender of the participants, the amount of inputted text, and the self-reported valence and arousal. While we did not control for all the variables in

this experiment, we believe these differences may be associated with different body postures during the typing task. For instance, participants with higher self-report stress levels may prefer a tenser upright seated posture and type with less overall pressure. In contrast, participants with lower self-reported stress levels may prefer a more relaxed slumped seated posture and type with more overall pressure.

Discussion

In a small controlled laboratory experiment, we found significant correlations between typing pressure and self-reported stress. In particular, we observed that differences in typing pressure across relaxed and stressful expressive writing tasks are correlated with differences in self-reported stress. While the sample size is limited both in number of participants and duration of the tasks, these findings are consistent with previous research considering similar activities in controlled desktop scenarios [12]. Thus, these preliminary findings seem to support that the same differences observed in more static desktop environments are generalizable to more dynamic and challenging smartphone interactions. As in previous work, we believe the increase of pressure is mainly associated with the increase of muscle tension of the stress response. However, more research is needed to identify if there are other influencing sources (e.g., distance between keystrokes and hands, changes of body posture during stress, different device handling behaviors). In addition, we have observed that overall typing pressure baseline is negatively correlated with self-reported stress. This finding is important as stress is very subjective and could be used to help develop person-specific models that automatically measure stress, as suggested by prior work [16][17]. Finally,

this work only considers pressure sensing but other metrics (e.g., keystroke duration, distribution of keystrokes) could be used to help build more robust stress sensing methods and better understand some of the observed differences. For example, we would like to analyze the error rate for both conditions in future studies. Future work will consider expanding the number of participants as well as study real-life settings in which the context of users is less constrained. It will also propose potential designs that leverage the findings of this work in meaningful ways.

Conclusions

This work shows results that support the possibility of using relative changes in pressure to capture cues of stress of smartphone users during typing. We are looking towards a future in which smartphones will offer a comfortable and passive sensing platform that helps support and promote our emotional well-being.

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