Utility of Haptic Data in Recognition of User State

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Abstract

The current paper examines optimal strategies for recognizing aversive user states such as frustration from users' patterns of pressure on a TouchPad. An experiment (N = 20) was conducted to compare the patterns of participants' pressure data between frustrating and baseline conditions when participants used computer-based instructions to complete a given task. Results showed that participants pressed TouchPad significantly harder when they were frustrated (M = 74.64, S = 16.04) than when they were not frustrated (M= 67.61, S = 15.70). Content analysis of facial expressions was compared with the haptic data for each participant. In general, the results showed a matching pattern in multimodal sensing methods. Implications of this study as well as the use of psychophysiological methods in the study of human-computer interaction are discussed.

1 Introduction

In spite of the recent development in the equipments and methodologies of psychophysiology, there are only a few empirical studies on user interfaces adopting psychophysiological methods (Ravaja, 2004). Turner (1994) defines psychophysiology as the "division of psychology" that examines causal relationship between psychological stimuli and physiological responses. Given the above definition, psychophysiological methods could be useful in detecting users' emotional states, especially when instant feedback is critical in interactive interfaces for human-computer interaction (e.g., computer-based support system, computer games, and learning software). In fact, Ravaja (2004) indicates the advantages of psychophysiological measures over traditional self-report. First, psychophysiological measures can be more objective in a sense, without being influenced by respondents' memory or social desirability. Second, psychophysiological measures can recognize subtle nature of the responses. Third, instant feedback with continuous data can be provided without interfering with message processing.

Therefore, the current paper investigates optimal strategies for recognizing aversive user states such as frustration from users' patterns of pressure on a TouchPad. Our goal is to develop acquisition techniques to observe and log patterns of the haptic data and integrate what we learn into an adaptive user interface that adjusts task difficulty and/or offers help functions dynamically when negative user states are recognized.

2 Related Work

2.1 Pressure and Frustration (Emotional Arousal)

Previous studies have demonstrated unobtrusive mechanisms for recognizing user states such as frustration based on the data from pressure-sensitive input devices (e.g., Mentis & Gay, 2002; Reynolds & Picard, 2001; Sykes & Brown, 2003). Mentis and Gay (2002) found a significant difference in participants' fingertip pressure on a Synaptics TouchPad before and after frustrating incidents in the context of word processing. Findings of this study suggest that haptic indicators (psychophysiological measures) may provide unobtrusive mechanisms for recognizing and responding to negative affective states of the user. Similarly, Sykes and Brown (2003) found that participants applied more pressure to the gamepad buttons as difficulty level increased in a video game, *Space Invaders*. However, there were some methodological offsets in these studies. For example, the operationalization of frustration was imprecise in the study by Mentis and Gay (2002), and causal link between user state and pressure applied to the gamepad was missing in the study by Sykes and Brown (2003).

Our study is distinctive in that we (1) embed manipulated frustration into the experimental design with a deficient set of instructions and resources for greater experimental control, and (2) analyze other multimodal inputs such as facial expressions for comparison with the haptic data.

2.2 Facial Expression and Frustration (Emotional Valence)

Emotions can be placed in a two-dimensional space, as coordinates of affective valence and arousal (Lang, 1995). The valence dimension refers to the level of pleasantness of an affective experience from unpleasant to pleasant. On the other hand, the arousal dimension refers to the perception of arousal associated with such an experience (Lavaja, 2004). The potential limitation of pressure data would be that it may not be able to detect the valence dimension of users' emotional state. For example, users may press a gamepad harder when they are frustrated and/or when they are excited. The patterns of pressure data may be useful in recognizing the arousal dimension of emotions such as excitement or frustration but may be poor at discriminating pleasant from unpleasant emotions, which is the affective valence dimension. To complement this potential limitation of pressure data, other multimodal measures that can identify users' different response patterns in the valence dimension such as facial expressions are needed (see Lavaja, 2004 for detailed information about studies in facial expressions). In the current paper, facial expressions of participants were videotaped and later analyzed in comparison with the patterns of pressure data.

3 Method

3.1 Experimental Design

A one-way within-subject analysis of variance (ANOVA) design was used to investigate the problem of multimodal sensing and fusion of sensory data streams in a laboratory environment. A content analysis was also used to compare the patterns of facial expressions with the pressure data. A total of twenty undergraduate students enrolled at a major west-coast university in the US participated in the experiment.

3.2 Procedure

Participants were scheduled to visit a laboratory where they individually performed a task of assembling LEGO pieces. Upon participants' arrival, an experimenter gave them a brief explanation about (1) rewards they would receive only when they finished the assembly task successfully within a seven-minute time limit, and (2) how to use a step-by-step instruction manual displayed on a laptop computer. Participants were allowed to consult a help site from the manual when they faced obstacles during their task. Finally, participants were debriefed at the end of the experiment and rewarded regardless of their performance.

3.3 Manipulation

The instruction manual consists of 13 steps including a photo of completed LEGO pieces for each step. The first six steps were designed in a way that participants could easily follow the instruction as a baseline condition. The next seven steps were designed to induce frustration to users as a frustrating condition.

User frustration was induced by three manipulations. First, participants were given a seven-minute time limit to complete the assembly task. A ticking clock was displayed on the top-right corner of the manual, which put more pressure on participants as time went on.

Second, participants were given deficient instructions in the middle of assembly (after the first six steps). Crucial steps were intentionally omitted from the manual. If participants consulted the manual, they were given correct information and rerouted to the proper step.

Third, participants had deficient resources for the task: they were not able to find a critical LEGO piece among the materials provided to them (there were more LEGO pieces than participants needed in order to make the finding process more frustrating). If participants asked for assistance from the help site, however, they were told how to find the missing piece. The purpose of the second and third manipulations was to make participants waste time in solving the unexpected problems and thus be unable to finish the assembly task in seven minutes.

In fact, only two participants could successfully complete the task within a seven-minute time limit. Even in these successful cases the participants reported their frustration during the experiment in post-experiment interviews.

3.4 Measure

TouchPad pressure data were captured every 10 ms in each step of the instructions and logged to provide a comparison record of different user states. Specifically, all the data points in each step were aggregated and averaged to represent pressure data per each step. Then, the pattern of pressure data from the first four steps (baseline condition) and from the last four steps (frustrating condition) were selected for each participant. Because each participant finished the task in different steps due to the time limitation, it was impossible to select the same steps over all the participants. Finally, pressure data was dummy coded for statistical analysis: 0 for non-frustrating condition (baseline); and 1 for frustrating condition.

Participants' facial expressions were also videotaped for a comparison with the haptic data. Two coders recorded participants' negative facial expressions independently. Coders were instructed to code minor changes in facial expressions as one and major changes as two. Holsti's (1969) reliability coefficient was used to test intercoder reliability. The formula for determining the reliability of data in terms of percentage of agreement is, (2M) / (N1 + N2), where M is the number of coding decisions on which two coders agree, and N1 and N2 refer to the total number of coding decisions by the first and second coder, respectively (Wimmer & Dominick, 1997). The results showed that two coders agreed 117 times. Holsti's coefficient for the content analysis was 90%, which is acceptable (Wimmer & Dominick, 1997).

4 Results

A within-subjects ANOVA was used to compare the patterns of pressure data between frustrating and baseline conditions. Results showed a significant difference in user pressure on the TouchPad, $F(1, 158) = 7.86$, $p < .01$. Participants' fingertip pressure was significantly greater when they were frustrated (M = 74.64, SD = 16.04) than when they were not frustrated (M = 67.61, SD = 15.70) (See Table 1).

Table 1: Comparison of Frustration and Non-frustration: Means, Standard Deviations, and Analysis of Variance

Measured Variable	Frustration Mean (S.D.) (n = 20)	Non-frustration Mean (S.D.) (n = 20)	F (1, 158)
Pressure data	74.64 (16.04)	67.61 (15.70)	7.86**

Note: ** $p < .01$ (2-tailed).

As shown in Figure 1 and Figure 2, the patterns of facial expressions were similar to the patterns of pressure data in each subject in general (due to the spatial limitation, we only show the comparison of two patterns in two subjects). Specifically, more frequent negative facial expressions were detected between 4.5 minutes and 6.5 minutes in Subject 7 (see Figure 1). The patterns of pressure data from the same subject also indicate more frequent and harder pressures on TouchPad between 4.5 and 6.5 minutes.

In Figure 2, negative facial expressions were recognized in three different time periods: (1) around three minutes; (2) about five minutes; (3) about seven minutes (toward the end). Similarly, the patterns of pressure data from the same subject show three major pressures in relatively same time periods (see Figure 2).

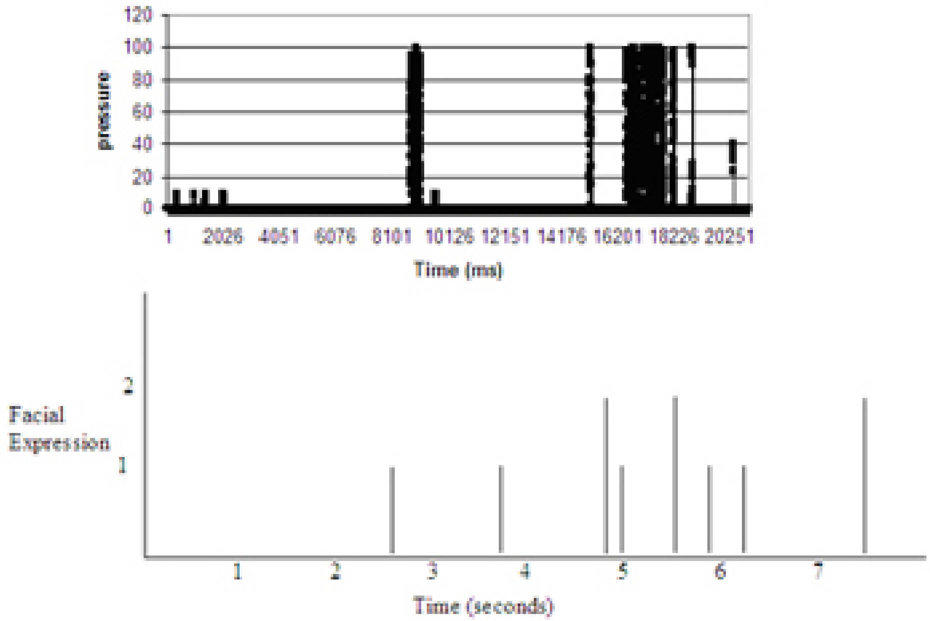

Figure 1: Comparison of the Patterns of Pressure Data and Facial Expression: Subject # 7

Note: Graph above shows the patterns of pressure data in timelines, logged automatically from TouchPad. Graph below shows the patterns of negative facial expression in timelines, coded manually by two coders (1 = changes of facial expression; 2 = severe changes of facial expression).

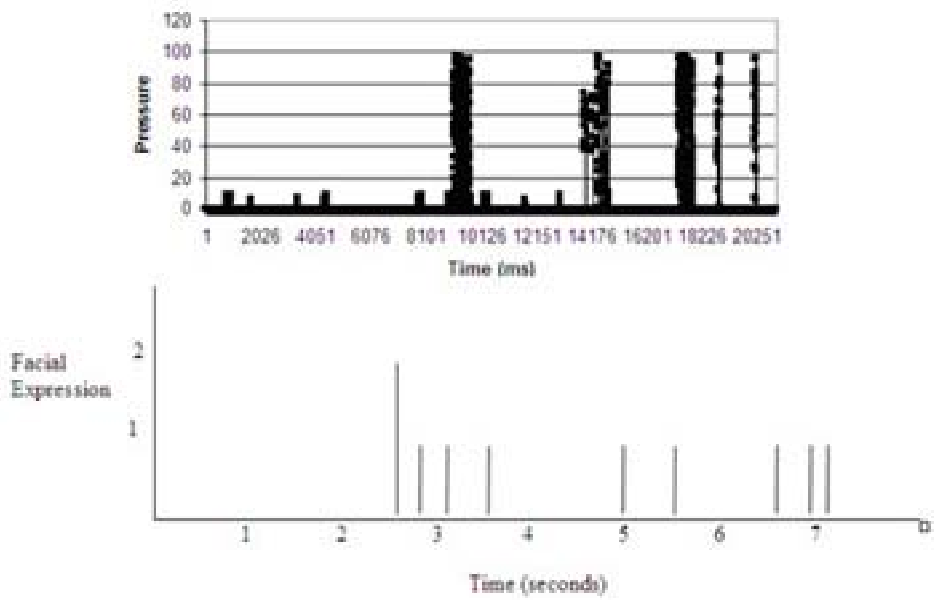

Figure 2: Comparison of the Patterns of Pressure Data and Facial Expression: Subject # 20

Note: Graph above shows the patterns of pressure data in timelines, logged automatically from TouchPad. Graph below shows the patterns of negative facial expression in timelines, coded manually by two coders (1 = changes of facial expression; 2 = severe changes of facial expression).

5 Discussion and Implications

The findings of the utility of pressure data implicate that users' emotional state such as frustration can be recognized automatically from the patterns of pressure on TouchPad (psychophysiological measure). Similar patterns of pressure data and facial expression confirm the validity of the measures used in this study and also indirectly suggest integration of multimodal sensing systems for developing future interactive interfaces in human-computer interaction.

Haptic data from the patterns of pressure on TouchPad can indicate changes in users' emotional state in the arousal dimension. When users are aroused, they tend to put more pressure on haptic interfaces (e.g., TouchPad). However, additional psychophysiological measures such as facial expressions are needed as complementary measures in order to provide a more accurate report of users' emotional state because of the affective valence dimension of emotions. The overall matching patterns of pressure data and facial expressions implicate that the two dimensions of emotions may not be separated, thus should be measured independently at the same time. Although we measured participants' facial expressions manually using the content analysis method, facial expressions can be measured automatically by using equipments such as facial electromyography (EMG). Facial EMG can identify emotional valence by assessing convert activity of facial muscles (Ravaja, 2004). For future study, it is recommended to use facial EMG and other advanced psychophysiological measures, in addition to haptic data, to develop more intelligent user interfaces that can provide users with automatic feedbacks or emotional responses.

Finally, with the ubiquity of interactive media, implications for measuring user states unobtrusively from multimodal raw sensory inputs are virtually unlimited. Haptic data has the potential to enable interactive systems to detect aversive user state dynamically and adjust system feedback to meet the needs of the individual user (McLaughlin, Chen, Park, Zhu, & Yoon, 2004). Sensing and fusion of data from haptics and speech or vision will shed further light on the design of dynamic user interfaces by allowing more tailored and personalized services to individual users in real-time applications such as computer-based customer service, learning software, and interactive computer games (see also Sykes & Brown, 2003). Finally, it is recommended that multimodal-sensing systems be developed because one psychophysiological measure may not be sufficient to identify a specific emotional response. Integrating multimodal data as well as situational data (e.g., in computer games when users are hit or losing continuously, any changes in the users' emotional state are likely to be negative rather than positive) can be complementary to each other and also to other measures such as self-report for recognizing users' emotional state in human-computer interaction.

6 References

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