Recognizing User State from Haptic Data

Margaret McLaughlin, Yi-Shin Chen, Namkee Park, Weirong Zhu, and Hyunjin Yoon
Integrated Media Systems Center
University of Southern California
Los Angeles, CA 90089 USA

ABSTRACT

An experiment was conducted to examine the utility of pressure and positional data from the Synaptics TouchPad to discriminating between baseline and problematic or frustrating user circumstances. Our special interest is in the problem of multimodal sensing and fusion of data streams from speech, haptics, and vision during acquisition of complex skills. In particular we are interested in finding optimal ways of combining raw sensory input to do user state sensing (e.g., emotions) and detect and forestall user errors or otherwise make appropriate adjustments during problematic situations, and also adjust system feedback to a level that best meets the needs of the individual user. This paper reports on our preliminary work on creating an emotion recognizer from the haptic data stream.

Keywords: User State Sensing, User Frustration, Haptics, Emotion Recognition, Adaptive Computing

1. OBJECTIVES

We wish to predict user frustration with computer-based tasks from the user's patterns of application of force to a pressure-sensitive input device, the Synaptics TouchPad. Our goal is to use the information from pressure on the TouchPad to train a classifier to recognize negative user affect, and ultimately to dynamically alter task environment (difficulty level, help level, etc.) to adjust to the current state of the user. More specific goals are as follows: (1) develop acquisition techniques for pressure data from the TouchPad that allow us to reliably describe normal patterns of positional and pressure data; (2) observe and log patterns of positional and pressure data under frustrating conditions; (3) from baseline and experimental conditions derive a model of positional and pattern differences which are predictive of negative user affective state and develop a function which reliably classifies new cases; (4) develop an adaptive user interface which adjusts task difficulty level and help functions dynamically when user frustration is recognized.

2. RELATED WORK

Previous Studies

Haptic indicators may provide unobtrusive mechanisms for recognizing and responding to negative affective states of the user. Mentis and Gay [1] found that differences in subjects' fingertip pressure on a Synaptics TouchPad were significantly greater before and after frustrating "critical incidents" in a word processing task than they were during comparable control incidents without frustrating episodes. Mentis and Gay emphasized that frustrating episodes were relatively infrequent, resulting in a small sample of data points. They argue for the use of more controlled data collection environments (e.g., deliberate induction of problematic situations) to study implicit user cues. Further, they note the importance of obtaining baseline measures on individual users if change data is to be employed. The study by Mentis and Gay and a related paper by Qi, Reynolds and Picard [2] have generated interest in the use of pressure-sensitive input devices to measure variations in muscle tension related to the experience of frustration in learning tasks. Qi, Reynolds and Picard used a Bayesian classifier, the Bayes Point Machine, to use mouse pressure data to reliably discriminate between episodes which frustrated users and those which proceeded smoothly. Mentis and Gay critique the work by Qi, Reynolds and Picard as having "technical problems" of an unstated nature and argue that it overemphasized pressure to the neglect of user clicks.

Sykes and Brown [3] studied pressure applied to an input device (analogue buttons on a game console) as an indicator of user emotion in the context of video gaming. In a variation on Space Invaders, Sykes and Brown created three difficulty levels which were presented in random order to the player. They found that as difficulty level increased, so also did the pressure applied to the gamepad buttons. Sykes and Brown noted certain defects in previous methods of assessing user state, such as GSR, whose measurements can be confounded by things like heavy perspiration or muscle tensing by the user. They note that GSR is not suitable for fast gaming, which requires rapid and dexterous finger movements. (Mentis and Gay argue that GSR measures and the like are too intrusive as well). Unfortunately, however, both arousal and emotion were unmeasured variables in the Sykes and Brown study, so some of the methodological gains were offset by a lack of design strategy for establishing a causal link between user state and pressure applied to the gamepad.

Our approach differs from these earlier efforts in several significant ways. In terms of the design of the experiments, we have a larger sample of data points. And rather than leaving frustration as an uncontrolled variable and inferring its presence from subjects' retrospective recollections, as in the Mentis and Gay study, or assuming that emotional arousal is isomorphic with task difficulty, as in the Qi et al. study, we build frustration into the design by providing the subject in the experimental condition with a deficient set of instructions for carrying out the assigned task, and follow up with a post-task validation of the experimental manipulation so that user affect will not be an unmeasured variable in the design.

3. PILOT EXPERIMENT

Procedures

In our pilot TouchPad experiment there were 9 subjects (1 woman and 8 men) who were graduate students working at an integrated media systems center at a large private research university in the US. The subjects were provided by an experimenter with a brief instruction about the experiment and then asked to assemble LEGO pieces following a set of pictures provided on a laptop computer screen. There were two assembly tasks. In the baseline task, the instruction manual contained a picture of a completed LEGO design, all the LEGO pieces needed, and pictures of 7 steps (one picture per each step) needed to complete the design. The 7 steps were so detailed that the subjects could easily finish the task if they followed the steps. From the task, baseline TouchPad pressure and positional data were captured and logged to provide a normative record of the user's patterns. A second task was designed to induce frustration in the user. Unlike the baseline task, there were 6 steps in the instruction manual in which three crucial pictures were not provided, and two pictured steps were presented twice. In addition, the color of the completed LEGO design was slightly different from that of the baseline task. That is, the second task was intended to make it difficult for the subjects to complete the design exactly as pictured. However, except for some missing steps and the different color of the completed design, other procedures were same as the baseline task. Five subjects began with the baseline task and then did the second task while the other four subjects started with the second task and then did the baseline task in order to avoid any possible order effect. TouchPad activity as the subjects interacted with the instruction manual on the laptop computer screen was sampled every 10 ms and logged for analysis. At the conclusion of each task the subjects were asked to fill out an online questionnaire, which was hyperlinked from the picture of the final step, with radio-button scaled responses and some open-ended questions which asked him or her to evaluate the pleasantness and ease of completing the task. TouchPad data from this evaluation task were also captured and logged every 10ms. In addition, the subjects' activity was videotaped so that their facial expression and verbalizations could be analyzed later. Finally, all subjects were debriefed and thanked.

Data Analysis

The online questionnaire was composed of 20 questions, each with a seven-point Likert-type response scale. Combining these 20 questions, a summed usability scale for the task interface was generated for each baseline and frustration condition. The usability scale for each condition was highly reliable (Cronbach's *alpha* for the baseline data: .92, *alpha* for frustration data: .96). Mean usability for the baseline condition (M = 4.75, SD = .73) was significantly greater than mean usability for the frustration condition (M = 3.36, SD = 1.10), $t(8) = 2.76$, $p < .05$). Subjects evaluated the baseline task interface more positively than that of the frustration task in terms of usability.

To examine our proposed approach, we employed the positional and pressure data collected from the 9 subjects. Based on our initial observation, the pressure data are more important than positional data; hence, we emphasized the pressure data in the following analyses. First, we intended to identify the important attributes by using PCA analysis. PCA [4,5] has been commonly used for dimension reduction and locating the important attributes (i.e., the principal components) in equal-length data.

Since the original data come in different lengths, we first employed Covariance Matrix Analysis to transform the original data into an 18×9 matrix where each row represents one sample. Next, we applied PCA to this matrix to obtain the principal components of these samples. Figure 1 shows the projection of the transformed TouchPad data to the 1st and 2nd principal components.

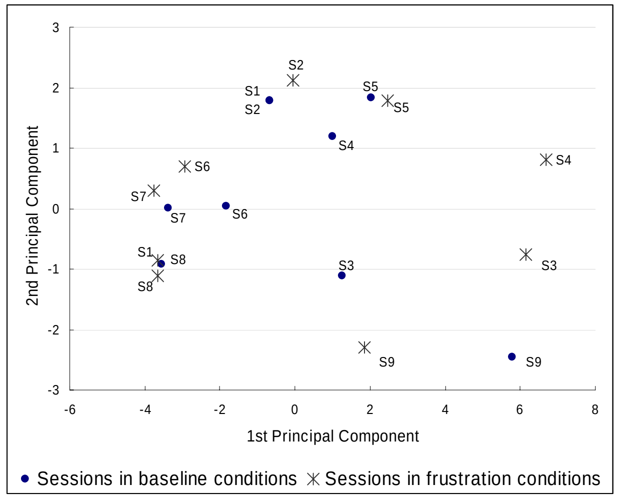

Figure 1 Projection of the transformed TouchPad data

We can observe that the 1st and 2nd principal components cannot distinguish the baseline and frustration samples; while for 5 out of 9 subjects their baseline and frustration samples are too close, the other 4 subjects (i.e., subject 1,3, 4, and 9) show relatively large variance between baseline and frustration samples. In other words, PCA failed to identify the important attributes of the collected time series.

Subsequently, we used FFT [6,7] to identify the frequency contents of the pressure time series. A common use of Fourier transforms is to find the frequency components of a signal buried in a noisy time domain. Figure 2 represents the frequency contents of the pressure data first for the baseline and and then the frustration condition.

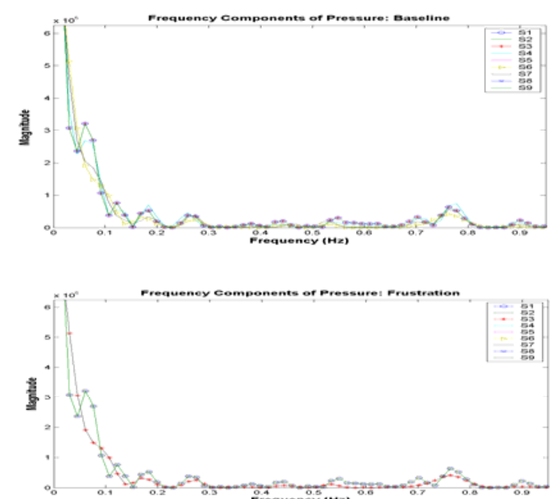

Figure 2 Frequency contents of the pressure data

Figure 2 illustrates that the frequency contents of the baseline and the frustration data are almost identical. It implies that FFT also failed to identify the important frequency attributes. In summary, because PCA and FFT cannot locate the important attributes for the classification, SVM would fail to classify the data without any comprehensive attribute as well.

To address this issue, we intend to employ some isolation techniques (such as the Ridge-Climbing heuristic [8]) to extract the frustration segments from the collected data. Currently, based on our observation, the users only expressed frustration at the end of the second task. Hence, the frustration data collected from the second task are in fact mixed with some baseline data. This might be the reason for the failure of PCA and FFT in recognizing the important attributes.

4. IMPLICATIONS

If we are successful in finding ways to measure user frustration unobtrusively from pressure on the TouchPad, and can develop algorithms for dynamic recognition of and rapid adaptation to user stress levels this work would be of considerable interest to makers of learning software in a variety of educational domains. Other researchers (Sykes and Brown) have speculated about the potential interest of game developers in such a result: (1) it would allow for adapting or creating new game content online in response to changing affective states of the user; (2) the user's current state could be made available to other players through variations in the player's avatar or screen character; (3) there is potential for the introduction of new 'game mechanics' based on user state.

5. ACKNOWLEDGMENTS

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6. REFERENCES

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