Subjective Difficulty Estimation for Interactive Learning by Sensing Vibration Sound on Desk Panel

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Abstract. In this paper, we propose a method which estimates the student's subjective difficulty with a vibration sound on a desk obtained by a microphone on the back of the desk panel. First, it classifies the student's behavior into writing and non-writing by analyzing the obtained sound data. Next, the subjective difficulty is estimated based on an assumption that the duration of non-writing behavior becomes long if the student feels difficult because he (or she) would not have progress on answer sheet. As a result, the accuracy of the proposed so simple behavior classification reaches around 80%, and that of the subjective difficulty estimation is 60%.

Keywords: subjective difficulty estimation, behavior classification.

1 Introduction

When a student studies alone and works through a lot of topics in a classroom, it is difficult for the student to correctly comprehend the proficiency level of each studied topic by herself (Fig. 1). As an example, let's consider a situation where the student works through dozens of math problems and reaches the correct answers. She will come to the conclusion that she has mastered the material and further review is not necessary. However, what if she can easily answer most of the questions, but has difficulty with others?In such case, she should review the topics of the difficult problems. However, it can be easily imagined that the student is unable to remember the difficulties of each problem herself. It is also difficult for a teacher to know how each problem is difficult for each student because the difficulty is psychological value, thus it cannot simply be measured by the score of an examination. If a teacher spends a substantial amount of time supervising the student, it might be possible to comprehend the subjective difficulty of each problem. However, teachers have to take care of dozens of students, thus it seems hard to do the same thing for all of them.

We give a solution to the issue with our proposed system which can estimate the subjective difficulty with each problem by observing the student's behavior based on the concept of "Ambient Sensing". Our proposed system measures the vibration sound on a desk panel, there by estimating the subjective difficulty of each problem in accordance with the measured sound, then saves it in a PC. Students can browse the subjective difficulty of each problem on a PC, and thus easily notice how well they actually understood the problems. Their teachers can also refer to the visualized subjective difficulty data on the PC.

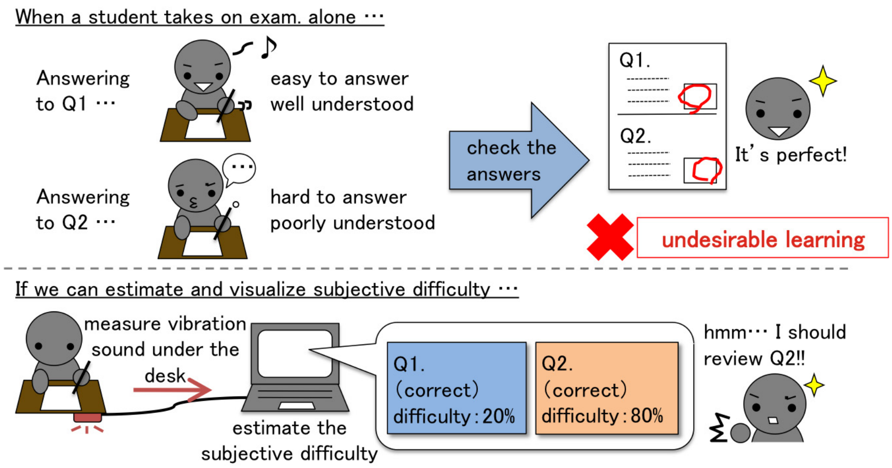

Fig. 1. The problem of studying by oneself and the advantage of our proposed system

2 Related Work

Our research is closely related to works on emotion estimation. Researchers have been investigating various emotions through physiological or behavioral measurements. The physiological measurement is reliable in the emotion estimation. However, this measurement cannot be performed in small classrooms or homes because large equipment is required. Furthermore, because sensors must be attached on the student's body, the sensors disrupt natural study. In the behavior measurement, image sequences captured by a video camera directed toward a student have analyzed the emotion estimation. Kappor *et al.* have investigated the estimated psychological stress of a student[1]. Their proposed system analyzed a student's facial expression, head velocity, and mouth movement from the captured images. Gunes *et al.* used two cameras to classify the participant's emotions into anger, disgust, fear, happiness, uncertainly and anxiety[2]. One was used for capturing a participant's facial expression, and the other was for upper body gestures. With the bi-modal information, they achieved over 94% classification accuracy. As described above, the camera-based approach could work well to estimate various emotions. However, especially in the case of estimating student's subjective difficulty, the approach would have a problem that the presence of camera might disturb the student's studying. Some of student might feel that they are being monitored by someone and consequently feel extra psychological stress.

Other behavioral measurement approach for emotion estimation exist. Okubo *et al.* proposed to estimate how a student concentrates on learning by analyzing data from a 3-axis accelerometer attached on the upper part of the backrest of a chair[3]. They assumed that little movement meant the student was concentrating. Because the student was unaware of the presence of the sensor, he (or she) did not feel any extra psychological stresses. However the system observed only the chair movement, and the obtained data was not sufficient to estimate the subjective difficulty of a question.

Lv *et al.* proposed to apply a pressure sensor keyboard which could measure finger pressures on the keys[4]. They classified the participant's emotion into neutral, anger, fear, happiness, sadness, and surprise from the measured pressure patterns. Luria *et al.* found that there was a difference between the handwriting of true and false sentences by analyzing pen pressure and trajectory measured by a pen tablet [5]. Although they worked well, keyboard and pen tablet are not widely used by students in studying at the moment. Instead, the conventional pen-and-paper based learning is still commonly applied in the school education.

Harrison *et al.* invented the system which was referred to Scratch Input. Scratch Input could detect the sound of scratching a textured surface with a fingernail and recognize several gesture patterns [6]. The authors applied two microphones and obtained the vibration sound occurring on the desk, and then, they recognized the user's gestures by analyzing the obtained sound. This would be able to apply to the study situation where the student uses a pen and paper because the sound of scratching with both a fingernail and a pen seems to be similar. Scratch Input was useful as the behavior estimation but it did not consider about estimating the user's emotion.

Compared to the previous works, we propose to estimate a student's emotion, in particular the subjective difficulty of a studied topic, in such a way that the student neither wears any sensors nor feels to be monitored. In addition, to allow the student to use the familiar pen and paper, the proposed system employs to measure the vibration sound on the desk.

3 Subjective Difficulty Estimation Method

3.1 Human Behavior Distinctive in Working on Difficult Topic

This section describes the proposed subjective difficulty estimation method. At first, we investigate what kind of behavior a student behaves when working on a difficult problem. Previously, Nakamura *et al.* carried out a user study in which a participant was observed when working on some difficult problems with a e-learning system. As a result, the authors found that the participant gazed one point on a PC monitor and did not click frequently for a long time. This result indicates that people tend not to move their bodies when they try to answer difficult problems to increase concentration.

In addition, we conducted a questionnaire survey where five high school teachers participated. On average the teacher have 14 years of experiment. We asked them the following two questions:

Q1. Can you comprehend how well your students understand each topic, only by observing their behaviors in an examination?
Q2. If Q1 is "yes", then which kind of behavior is the most important key for you to estimate their proficiency levels on the topic?

In terms of Q1, four participants answered that they could comprehend their students' proficiency levels, not completely but partially. In terms of Q2, all four teachers told that they focused on how fast their students solve each problem. When students understand a topic, they can answer related problems quickly, and vice versa.

3.2 Ambient Sensing

We apply the "Ambient Sensing" approach to our subjective difficulty estimation system. The "Ambient Sensing" approach measures human behavior by using sensors embedded in a natural environment so that the user does not notice the presence of the sensors. Thus a student neither feels to be monitored nor wears/holds any special devices. The proposed system estimates the subjective difficulty in a usual learning environment where a student uses a pen and paper on a desk.

We focus on the vibration sound on the desk. When a student is writing an answer to a question with a pen, the pen hits the desk through the paper and consequently the desk vibrates. We measure the vibration as sound by attaching a small microphone on the backside of the desk. We analyze the sound data to detect whether the student is writing, and then estimate the subjective difficulty of the current question.

3.3 System Configuration

Figure 2 shows our first prototype system. We prepared a ballpoint pen and a desk (500 × 400 × 670 mm) whose top was chiefly made of wood. As described in 3.2, we attached a small piezoelectric microphone (27 mm radius, less than 1 mm thick) on the backside of the desk. A PC analyzed the measured sound data and estimated the subjective difficulty. The sound data was amplified before sent to the PC.

3.4 Handwriting Estimation

We set the assumption that a student repeats two states, the THINKING-STATE and the WRITING-STATE, while studying, as shown in Fig. 3. As a preliminary stage of the subjective difficulty estimation, we propose to distinguish THINKING-STATE from WRITING-STATE by analyzing the measured

Fig. 2. Overview of prototype system

sound data. Output of this processing, "Handwriting Estimation", is handled to the next stage, "Measure Subjective Difficulty", which is indicated in the next section.

Figure 4 shows the classification tree applied to the measured vibration sound data. The measured data is at first classified into the SILENCE class and the SOUND class. The data falling into the SOUND class is then classified as the WRITING-SOUND class and the NOISE class. We only consider the WRITING-SOUND case when collision and friction sounds are made by a pen on paper. The other sound which occurs when the student does not write anything is regarded as the NOISE (e.g., the friction sound of the paper or the student's hand with the desk). We refer to the SILENCE and the NOISE classes together as the NON-WRITING-SOUND class. The proposed sound classification is related to the two states of Fig. 3. The THINKING-STATE corresponds to the NON-WRITING-SOUND class, while the WRITING-STATE corresponds to the WRITING-SOUND class.

The vibration sound on the desk is measured as a monaural signal with the sampling frequency of 44,100 Hz. The measured sound is downsampled to 11,025 Hz, and then its Fourier transform is computed. We analyze the frequency characteristics of the measured sound data to classify it into the proposed sound classes. As a preliminary study, we measured vibration sounds on the desk in the following conditions: (1) a participant wrote texts with a pen and paper on the desk (i.e., WRITING-SOUND), (2) she did not write anything but did other things such as tapping with her finger or sliding the paper on the desk (i.e., NOISE), and (3) nothing existed on the desk (i.e., SILENCE). As a result, we found that there were differences in the spectra at frequency band of 200–250 Hz and 1,050–1,130 Hz between WRITING-SOUND and NON-WRITING-SOUND. Figure 5 shows the spectra of each sound class. Thus, we use the means and variances of the spectra at these two frequency bands to classify the vibration sound

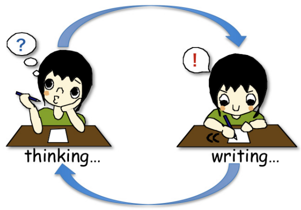

Fig. 3. Student's behavior model when she is working through a problem

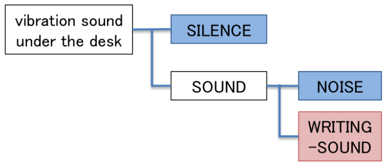

Fig. 4. Classification tree of vibration sound on the desk. We refer to the classes SILENCE and NOISE as NON-WRITING-SOUND respectively, whereas WRITING-SOUND.

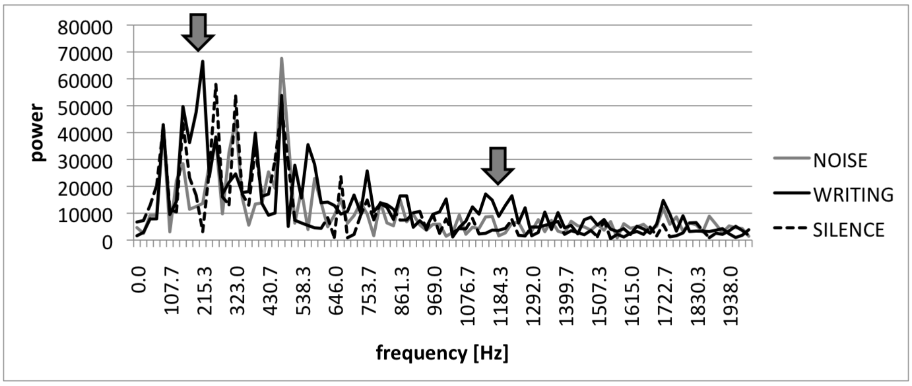

Fig. 5. The spectra of NOISE(gray solid line), WRITING-SOUND(black solid line), and SILENCE(black dot line)

into WRITING-SOUND and NON-WRITING-SOUND. We apply a decision tree for the classification.

3.5 Measure Subjective Difficulty

To investigate the relationship between subjective difficulty and writing behavior, we observed a few studying students working on a series of calculations in a classroom. As a result, they often stopped their writing hands when they worked through difficult problems. This was regarded that the students tend to be more in the THINKING-STATE than in the WRITING-STATE then. Thus, we define the ratio of the duration of the NON-WRITING-SOUND to the total amount of time spent for a question as the subjective difficulty of the question. Suppose that the WRITING-SOUND duration is W_t and the non-writing-sound duration is N_t, the ratio R is computed as:

$$R = \frac{N_t}{W_t + N_t}. \quad (1)$$

4 Experiment

4.1 Evaluation of Hand-Writing Estimation

We constructed a decision tree to classify the captured vibration sound into WRITING-SOUND and NON-WRITING-SOUND based on algorithm C4.5. Five subjects were recruited from the local university (age 24.2 ± 2.2 years, mean ± SD; 3 female, 2 male) and were requested to work on simple calculation problems on a paper using MVPen[1] to answer the problems. MVPen is a ballpoint pen equipped with a sensor which can detect whether it touches the paper, its sampling rate is 211.06 Hz. The touch information obtained from MVPen could be regarded as reference. We prepared sixty different problems for each subjects.

When each subject worked through the calculations, the vibration sounds on the desk were captured by the microphone and the touch information obtained from MVPen were recorded. Time series of the captured sound data was segmented in such a way that the duration of each segment was 1/211.06 s, and then each segmented was classified into the WRITING-SOUND and the NON-WRITING-SOUND classes by using the reference. For each segment, four feature values were calculated: the mean and variance values of the spectra at the frequency bands of 200–250 Hz and of 1,050–1,130 Hz. Using these parameters, we made a decision tree based on C4.5.

We carried out an evaluation of the decision tree. We computed the accuracy of the classification by using the same sound data. Figure 6 shows the accuracy averaged within each participant and that among the participants. As a result, 80.6% of the WRITING-SOUND and 82.2% of the NON-WIRITING-SOUND were classified correctly on average.

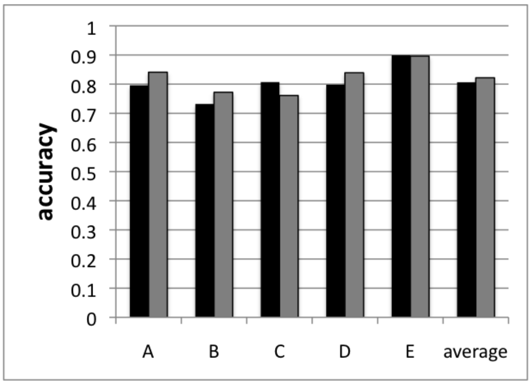

Fig. 6. The classification accuracy of vibration sound when the each five subjects marked a correct answer. The accuracy of the WRITING-SOUND is colored by black, and gray bar shows the accuracy of the NON-WRITING-SOUND.

[1] MVPen Technologies Ltd. (http://www.mvpen.com/)

4.2 Evaluation of Subjective Difficulty Estimation

We evaluated the proposed subjective difficulty estimation method described in Sec. 3.4 by conducting a user study. We prepared three math problems of different difficulties (linear equation, simultaneous equation, and quadratic equation). A subject tried to solve them in a random order. The subjective difficulty of each problem was computed by Eq.(1). We also asked the subject to report the subjective difficulty of each problem, according to a 5-point Likert scale from 1=*very easy* to 5=*very difficult*, just after he (or she) solved it.

Ten university students (6 male, 4 female) participated in the study. As a result, the order of the three problems according to the computed subjective difficulty and that to the reported subjective difficulty corresponded in six subjects' data. Figure 7 shows the computed and reported subjective difficulties of the problems of three subjects. Figure 7 (a) and (b) show the similar characteristic, while Fig. 7(c) shows the other type.

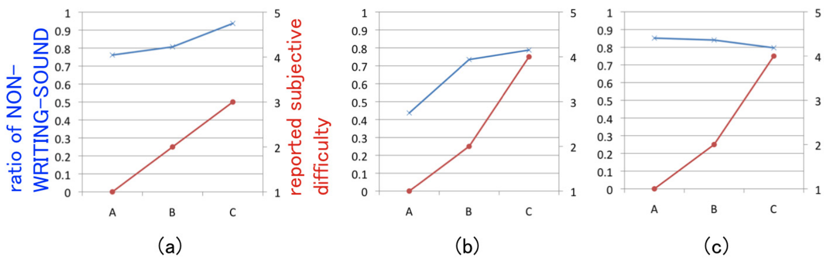

Fig. 7. The evaluation result of subjective difficulty estimation of three subjects. The line with cross dots shows the ratio of NON-WRITING-SOUND, and the line with circle dots shows reported subjective difficulty.

5 Discussion

It is regarded that one of the reasons why handwriting estimation accuracy was around 80% was the difference in writing pressure among the subjects. In the current implementation, the measured sound data was processed with a single decision tree which was constructed regardless of the subject's differences. Therefore the estimation accuracy would be degraded. Preparing different decision trees for different students would be the solution for this problem.

From the result of the evaluation conducted in Sec. 4.2, we confirmed that the correct subjective difficulty could be estimated for 60% of the subjects. Although there might be several reasons for the low accuracy, we think that this is mainly caused by the difference in behavior among individual subjects and by uncertainty of reported subjective difficulty as true value.

We employed the ratio of the duration of the NON-WRITING-SOUND to the total amount of time spent for a problem as the subjective difficulty, but this measure might not be universally applied. The behavior of a student who is working through a difficult problem is different among individuals. When deeply thinking about the problem, some students would stop moving their pens while others would tap their pens on the desk frequently. We designed the current system by taking into account the former case, so the later students are not supported. We will further investigate the behavior of students when they are working through difficult problems, and apply other distinctive features to estimate the subjective difficulty.

It takes a lot of time to develop an algorithm for individual identification because measurement and analysis of a great amount of data are needed in advance. Once the algorithm is developed, it is regarded that this technology could be efficient for application and the possibility of application would be widen. For example, a personalized study support will be available as we mentioned in Sec. 1. With the support system, it is also possible that controlling difficulty level of a problem and suggesting heavy review on the point where a student does not understand enough.

Furthermore, it is regarded that physiological measurement is significant to get the subjective emotion. It is generally said that emotion should be evaluated by the three measurements holistically; physiological, subjective, and behavioral measurement. Our research evaluates only subjective measurements reported by questionnaire. This seems to have a problem, the emotion which occurs for a moment on while the student is working through a problem might not be reflected in the questionnaire. This is because emotion is transient and is not memorized all of the time. If we apply the physiological measurement, the estimation accuracy would improve and we would be able to get hints for estimating other emotions because of obtaining the unconscious signal which could miss reported from questionnaire. However, a special equipment should be prepared to obtain physiological measurement. It is regraded that such measurement usually let subjects feel a kind of restriction because of sensor the user wears occurs a subject an extra stress which influences to his or her real studying. Thus we do not apply the physiological measurement in an ambient way.

To measure subjective emotion is supposed to obtain physiological measurement such as brain wave, it is difficult to apply it when students study in their classroom or home in general. A teacher also may not be able to observe all his students all the time. Therefor, we regard that the potential of the proposed approach is to estimate subjective difficulty by observing student's study all the time with only one microphone. This sensing environment is simple so that students must not feel any extra stress and could keep their natural study.

6 Conclusions

In this paper, we proposed a system which estimates the subjective difficulty of the student. First, our system obtained the vibration sound on the desk and analyzes the sound data. The student's behavior was classified into the WRITING or NON-WRITING categories. At last, the subjective difficulty was estimated by the ratio of NON-WRITING-SOUND.

As for future work, we will try to estimate not only subjective difficulty but also other subjective information such as uncertainly for a question. We will also apply other sensors to estimate the subjective difficulty more correctly.

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