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Real-time Estimation of Learners' Mental States from Learners' Physiological Information Using Deep Learning

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Abstract: It is important to know the mental states of learners during the learning process to improve the effectiveness of teaching and learning. In this study, we first extracted the relationships between learners' mental states and teachers' speech acts, as well as learners' physiological information, by constructing a deep learning system. The physiological indexes were near infrared spectroscopy (NIRS), electroencephalography (EEG), respiration intensity, skin conductance, and pulse volume. Learners' mental states were divided into nine categories in accordance with the Achievement Emotions Questionnaire. In our experiment, the system achieved a high accuracy in predicting the learner's mental states from the teacher's speech acts and the learner's physiological information. A mock-up experiment was then conducted, which revealed that the system's interface was able to support teaching and learning in real time.

Keywords: physiological information, deep learning, emotion estimation, Achievement Emotions Questionnaire, learning support

1. Research Background and Objective

To improve the effectiveness of teaching and learning, it is substantially important to know the mental states of learners during the learning process. Fundamental studies in educational technology have revealed a lot about the relationships between learners' physiological information and acts and their mental states. Thus, in this study, we developed a deep learning system that could estimate the mental states of learners from multifaceted information of their learning. The possibility of providing real-time support to learners using the system's interface was also tested and discussed.

2. Literature Review

Matsui & Takehana (2015) investigated the relationships between learners' physiological information and acts and their mental states. They formalized how the teacher's speech acts, learners' physiological information, and learners' mental states interacted. On the other hand, Horiguchi, Kojima, & Matsui (2010) developed a model and fundamental technique that estimated learners' comprehension and psychological states using machine learning, which could promote the realization of automatic mentoring. They put forward a difficulty evaluation system based on the low-level interaction resource proposed by Ryu & Monk (2004), which consisted of finely sampled action attributes. However, problems such as optimization of neural network training and methods of obtaining learners' psychological states still remained.

3. Experiment for Obtaining Multifaceted Information of Learning

One teacher and one student from a private tutoring school participated in the experiment. We measured the physiological information—the pulse volume, respiration intensity, skin conductance, brain blood flow (using near infrared spectroscopy [NIRS]), and electroencephalography (EEG)—of the learner during a class, which was conducted in the usual manner. While watching the video recording of the class, we used an application that we developed to divide the teacher' speech acts into nine categories—Explaining, Questioning, Comprehension Checking, Repeating, Praising, Alerting, Task Fulfillment Checking, Chatting, and Others—following the same procedure as Matsui and Takehana (2015). We also divided the student's mental states into nine categories—Enjoy, Hope, Pride, Anger, Anxiety, Shame, Hopelessness, Boredom, and Relief—in accordance with the Achievement Emotions Questionnaire (Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011).

On a later day, the student was asked to watch the video recording and, using the aforementioned application, report how her mental states changed during the class. On the other hand, the teacher was also asked to watch the video recording but predict the change in the student's mental state. Across the nine mental state categories, the consistency between the student's introspective report and the teacher's prediction was 24.11%.

4. Analysis by Deep Learning

Here, we introduce the deep learning system that we constructed to extract the mappings between the student's physiological information and mental states in the experiment (mentioned in Section 3). This system had five inputs—the teacher's speech acts and the student's skin conductance, pulse volume, respiration intensity, and NIRS—while the outputs were the degrees of the nine mental state categories. For ease in practice, we did not perform preprocessing, such as bandwidth averaging of NIRS data and data standardization, except for equalizing the granularity of the inputs through interpolation because of their different sampling rate.

The system comprised a six-layer perceptron: an input layer, four hidden layers, and an output layer. The first hidden layer was adjusted to include 69 nodes, the second 89 nodes, the third 80 nodes, and the fourth 69 nodes.

TensorFlow (version 0.12.1) for Python 3.5 was used to implement the system. The training data for each inter-layer mapping was used for 70,000 iterations. The activation functions were the tanh for the hidden layers and the softmax for the output layer. Cross-entropy error was the cost function, while the optimization method was the gradient descent. The learning rate was set to at 0.08. A cross-validation was run 10 times, with 60 percent of the data used as training data and the remaining 40 percent as validation data.

As a result, the system estimated the student's mental state from the physiological information to accuracy of 76.17%, which was far higher than the 24.11% of the human teacher's prediction. This suggests that the system can provide support to teaching and learning.

5. Mock-Up Experiment on Real-time Assistance in Teaching and Learning

A mock-up experiment was conducted to evaluate the ability of the deep learning system in providing real-time support for teaching and learning. This experiment aimed to verify whether the teacher changed her acts according to the information obtained through the system's interface.

One teacher and one student participated in the experiment, which consisted of four 10-minute classes. After each class, an interview was conducted to test the effectiveness of the system's interface. For ease of reading, we designed the interface to display a "positivity score" and a "negativity score." The former totaled the degrees of the mental state categories Enjoy, Hope, Pride, and Relief, and the latter those of Anger, Anxiety, Shame, Hopelessness, and Boredom. These degrees were determined and input into the interface manually, rather than computed by the system from real-time measured physiological information. The displayed positivity and negativity scores were updated every 2.5 seconds.

From the interview results, we discovered that the teacher was unable to see the system's interface when providing explanations. Therefore, it is necessary to use vibrations that would alert the teacher to changes in the positivity and negativity scores. From interviews to the teacher, the results did reveal that the teacher adjusted her teaching strategies according to the displayed scores in an attempt to improve the student's comprehension. This implies that the system was effective in assisting teaching and learning in real time.

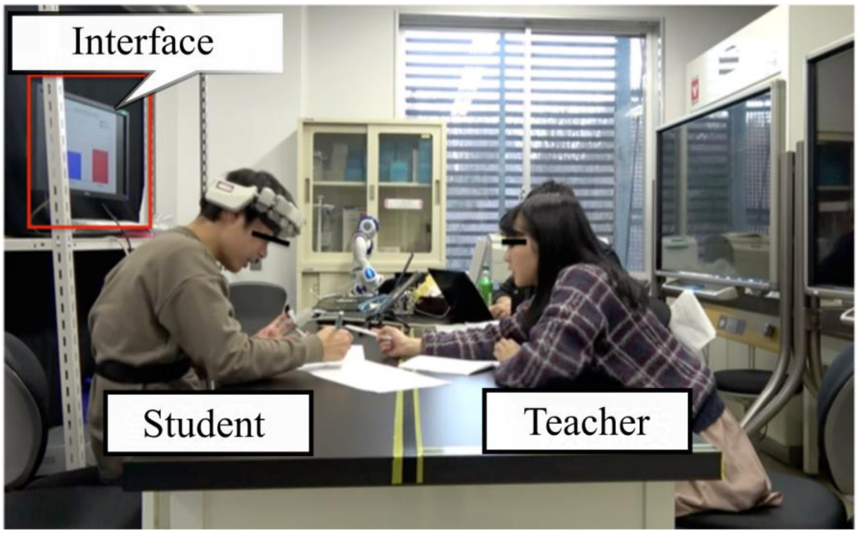

Figure 1. The setting for the mock-up experiment and the configuration of the deep learning system's interface

6. Summary and Implications for Future Work

First, we conducted an experiment to obtain multifaceted information of learning using physiological information measuring instruments. The data was preprocessed and analyzed by constructing a deep learning system, which was able to estimate the student's mental state to an accuracy of 76.17%. Then, we conducted a mock-up experiment, the results of which suggested that the system's interface was effective in supporting teaching and learning in real time.

However, there still remain problems in optimization of the multilayer perceptron training and with the user experience. The results of the mock-up experiment revealed that the physiological information measuring equipment needs to be simplified, and that the location and display of the system's interface should be more convenient for the teacher (e.g., vibrations could be used to notify the teacher of any change in the displayed positivity and negativity scores).

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