Confusion State Induction and EEG-based Detection in Learning

Yun Zhou, *Member, IEEE*, Tao Xu, *Member, IEEE*, Shiqian Li, and Shaoqi Li

***Abstract*—Confusion, as an affective state, has been proved beneficial for learning, although this emotion is always mentioned as negative affect. Confusion causes the learner to solve the problem and overcome difficulties in order to restore the cognitive equilibrium. Once the confusion is successfully resolved, a deeper learning is generated. Therefore, quantifying and visualizing the confusion that occurs in learning as well as intervening has gained great interest by researchers. Among these researches, triggering confusion precisely and detecting it is the critical step and underlies other studies. In this paper, we explored the induction of confusion states and the feasibility of detecting confusion using EEG as a first step towards an EEG-based Brain Computer Interface for monitoring the confusion and intervening in the learning. 16 participants EEG data were recorded and used. Our experiment design to induce confusion was based on tests of Raven's Standard Progressive Matrices. Each confusing and not-confusing test item was presented during 15 seconds and the raw EEG data was collected via Emotiv headset. To detect the confusion emotion in learning, we propose an end-to-end EEG analysis method. End-to-end classification of Deep Learning in Machine Learning has revolutionized computer vision, which has gained interest to adopt this method to EEG analysis. The result of this preliminary study was promising, which showed a 71.36% accuracy in classifying users' confused and unconfused states when they are inferring the rules in the tests.**

I. Introduction

Emotions that are generated during learning, sharing the neural circuitry with cognitive activities, impact the learning positively or negatively. Among these emotions, confusion occurs commonly during learning and has been proved beneficial for learning [1]. Confusion refers to the state that is triggered when learners are confronted with information that is inconsistent with existing knowledge and learners are uncertain about how to proceed [2]. This cognitive disequilibrium occurs when an individual confronts with impasses, the frequency of which is not low. Once the confusion is successfully resolved, the learning and comprehension at a deep level is generated.

In a conventional class, a human teacher could easily capture the confused state of students and help them resolve the confusion via adjusting the contents and examples of the lecture. Current online courses platforms or Intelligent Tutoring Systems show the popularity, however, they are far away from detecting students' cognitive and affective states, delivering effective pedagogical strategies and offering adaptive instruction.

In recent years, quantifying and visualizing the confusion that occurs in learning as well as intervening have gained great interest by researchers [3][2]. Among these researches, measuring confusion is the critical step and underlies other research work. The ways that have been used to measure affective states in digital environments could be mainly categorized into three ways according to the data acquisition method: questionnaire-based measures, physical measures and physiological measures. Questionnaire-based measures are composed of self-reported measures and observers' reports, which are subjective measures and used the most commonly. Many verbal scales have been designed to assess the cognitive or affective states. Besides, Self-Assessment Manikin scales are pictorial rating scales, which are widely used to measure emotions on the valence and arousal dimensions [4]. Physical measures and physiological measures have been investigated increasingly due to the objectivity and the ability of real-time monitoring. Physical measures include the detection of the facial expression [5], gestures and postures [6], the interaction analysis, etc. Compared with physical measures, physiological measures are direct and could assess the internal features of an individual. With regard to brain activities, Electroencephalograph (EEG), functional Near Infrared (fNIR), and functional Magnetic Resonance Imaging (fMRI) have been used to monitor variation and trends of emotions.

Commercial EEG data acquisition devices have a relatively cheaper price and EEG has a good temporal resolution, which are appropriate for being applied in the education. The classification methods of current EEG-based Brain Computer Interfaces for emotion recognition systems have been based on either machine learning algorithms like Support Vector Machine [7], or the estimation of time-varying features [8]. Filter bank common spatial pattern (FBCSP) is one of the classical methods to analyze EEG data [9]. The main idea is: the first getting different frequency bands by separating raw EEG data signal, then extracting features from frequency bands, and finally classifying based on these features. Those methods that are employed to process EEG data require the stages of artifacts removal, feature extraction, and feature selection. End-to-end deep learning [10] method can take all these multiple stages, and replace them usually with just a single neural network. It reduces the process of feature

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Y. Zhou (Corresponding author) and S. Li (Shiqian Li) are with the School of Education, Shaanxi Normal University, Xi'an, 710062, P.R.China. Corresponding author's phone: +86-29-85308047, fax: +86-29-85308047 (e-mail: zhouyun@snnu.edu.cn, qc@snnu.edu.cn)

T. Xu and S. Li (Shaoqi Li) are with the School of Software and Microelectronics, Northwestern Polytechnical University, 127 West Youyi Road, Xi'an, Shaanxi 710072, P.R.China. (e-mail: xutao@nwpu.edu.cn, lsqylxq@163.com)

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extraction. According to learning from raw EEG data, it can map them directly to objectives.

In this work, we investigated the induction of confusion and the feasibility of detecting confusion using EEG as a first step towards an EEG-based Brain Computer Interface for monitoring the confusion and intervening in the learning. Our experiment design to induce confusion was based on Raven's Standard Progressive Matrices, including 16 participants' effective data. Each confusing and not-confusing test item was presented during 15 seconds and the raw EEG data was collected via Emotiv headset. An end-to-end classification method has been applied. Results from our work were promising, showing 71.36% accuracy in classifying users' confused and unconfused states, which achieves our expectations.

II. Confusion Recognition System Architecture

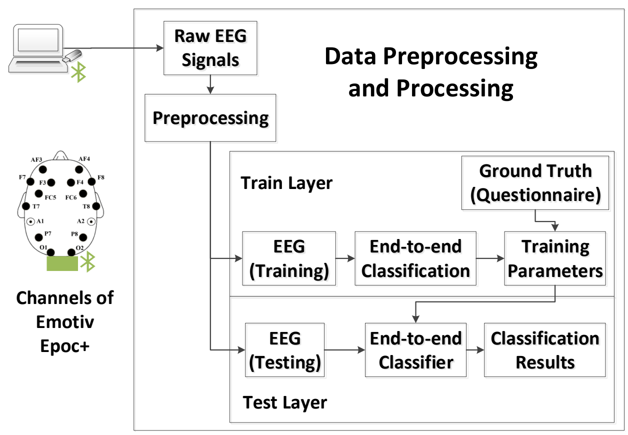

Fig. 1. The architecture of EEG-based confusion recognition system.

As shown in Figure 1, we have proposed the architecture of EEG based confusion recognition system. This system contains three steps: raw EEG signals recording, data preprocessing, and classification.

In this work, Emotiv Epoc+ is employed to collect raw EEG data related to different confusion states, which is a commercial EEG device to measure human brain's activities, and cognitive and emotional states designed by Emotiv. The Emotiv Epoc+ is a portable wireless acquisition system connecting to a computer via a USB dongle and recording raw EEG data via a headset. The neuro-headset features 14 channels (AF3, F7, F3, FC5, T7, P7, O1, AF4, F4, F8, FC6, T8, P8, and O2) plus 2 references (A1 and A2) based on the 10-20 format. Epoc+ is low-cost and ubiquitous, which has been showed the feasibility among researches to access cognitive activities [11]. All 14 electrodes were used and the data was collected.

With regard to preprocessing, we cut the data into one piece of 15 seconds and labeled with actual labels. We first assigned labels to each stimulus before the experiment through a pilot test as stated below, in order to well-organize the experiment. In our experiment, after viewing test pictures, we asked participants to report their confusion states for every picture and obtained the actual labels for training and testing the classifier. This is to avoid the situation that the stimulus materials were supposed to be confusing but participants found not confusing and vice versa.

The data processing is mainly based on the end-to-end deep learning algorithm. Although the commercial devices are portable, the signals obtained from such devices are not as precise as that of the medical EEG acquisition devices. Thus, the traditional method cannot easily extract valid features to classify. Since the event lasts a period of time, under the same experiment condition, we assumed that the noises are consistent with the similar probability distribution. Benefiting from deep learning [10][12], we adopted a convolutional neural network (CNN) to detect confusion state directly. Compared with traditional methods, this method choses raw data from different channels as input directly, which reduces the process of transforming the EEG raw data into the standard frequency bands and the process of extracting features. It can classify whether the individuals are confused or not confused directly. Our method provides an alternative method to handle EEG data with low precision. Figure 2 shows the main structure of this method. The core of this method is CNN. It consists of three layers: two convolutional and pooling layers, and one full-connected layer. Since Emotiv has 14 EEG channels and scanning sequence is roughly 200 times per second, we converted one second to the matrix of 14x14x14 as input data. The labeled data in our experiments indicates the confusion states, that is, confusing or not confusing. Accordingly, the implementation of machine learning approach based system typically includes two phases: training and testing.

III. Experiment Design

In this section, we present the experiment design, including the participants' demography, the design of stimulus and the procedure of the experiment.

A. Participants

The main procedure in this experiment is presented as follows. The tester greeted the participant, and introduced this study and explained the procedure briefly. Then the tester asked for the permission of using the recorded EEG data for the research purpose and the data obtained in the questionnaire. After the participant watching stimulus, he or she was asked to fill out questionnaire and gave the explanation of his or her choices.

Seventeen college students participated in this experiment, while one's data was ejected due to an unexpected disruption occurring when this participant watching the stimulus. Therefore, sixteen participants' data were effective and kept to process. In total, we had 2 male and 14 female participants. Their ages were distributed between 23 and 34, with mean of 24.69 (SD = 2.65 years). Most of the participants were postgraduates and studying in the university.

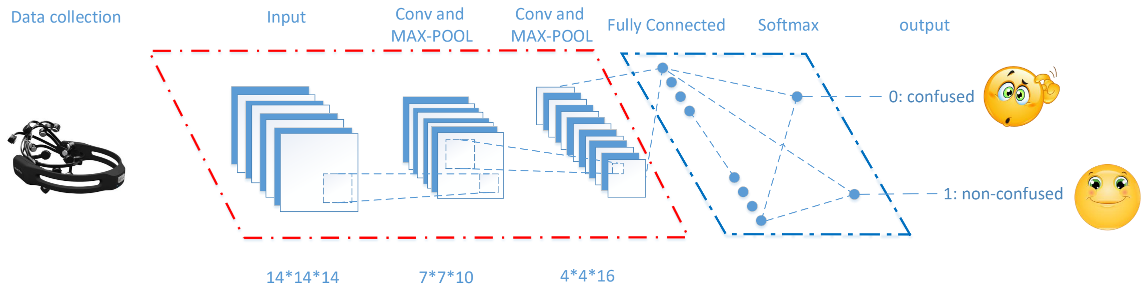

Fig. 2. The main structure of end-to-end learning model.

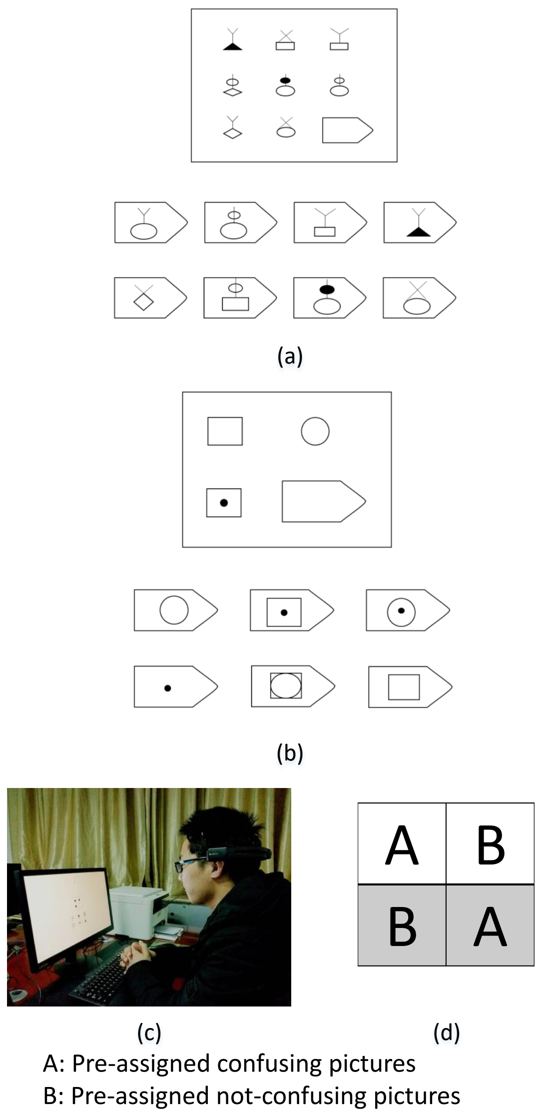

Fig. 3. Experiment design. (a) An example problem at a hard level similar to those from the Raven's Matrices family of tests to induce confusion. (b) An example problem at an easy level similar to those from the Raven's Matrices family of tests to induce not-confusing mind state. (c) The user is watching the picture stimulus wearing Emotiv Epoc+ headset. (d) Latin Square for counterbalancing the learning effects.

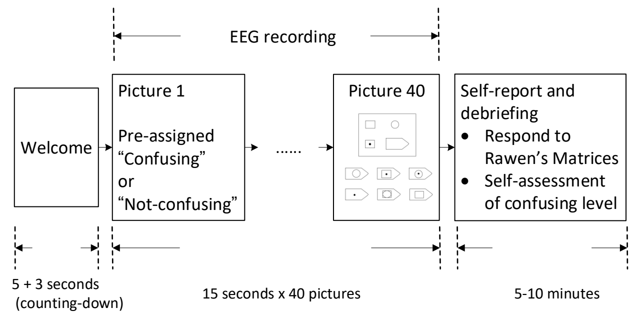

Fig. 4. The procedure of the experiment.

B. Confusion Induction and Stimulus Design

In the study of confusion detection, confusion induction is a daunting task. The effectiveness of confusion induction determines the success of classification. We adopt the tests of Raven's Matrices to induce confusion but change the presenting order to meet the requirement of our experiment. Raven's Standard Progressive Matrices (Raven's Matrices or RPM) is a nonverbal group test typically used in educational settings to measure the taker's abstract reasoning ability [13], which is administered to the groups ranging from 5-year-olds to the elderly. The original test of Raven's Matrices consists of increasingly difficult pattern matching tasks, which has little dependency on language abilities.

For reasoning test, the levels of confusion would decrease by the longer interval, while the confusion state is susceptible to be triggered in a short interval. Thus, before the actual experiment, we did a pilot test to identify whether the Raven's test pictures can induce confused or unconfused states, and determine the interval of presentation of each picture as 15 seconds. When presenting each picture 15 seconds, we assumed that half of 40 the pictures which are hard to deduce would be confusing and the rest of them which are easy to deduce would be not-confusing. Then we assigned the labels to these stimuli, which were divided as into two groups: confusing picture group (named as A) and not-confusing group (named as B). A within-subjects design was employed, in which all participants watched 20 pre-assigned confusing (see Figure 3(a)) and 20 not-confusing pictures (see Figure 3(b)). The order of two groups that was presented for participants was counterbalanced with a 2×2 balanced

Latin square [14]. In each test item, the subject was asked to identify the missing element that completes a pattern in 15 seconds. The pattern that was used in this experiment was in the form of a 3×3 or 2×2 matrix.

C. Procedure

In the task, each participant was asked to watch the stimulus presented by E-Prime and fill out the questionnaire after finishing watching (see Figure 4). The welcome picture was present in 5 seconds, followed by a counting-down of 3 seconds, which reminded the participant to be ready for the test. When performing the reasoning task, the participant was instructed to keep the still except blinking and open the eyes to view each picture presented and deducted the pattern should be matched. In this process, the EEG data was recorded (see Figure 4) via one laptop and the stimulus was presented via another computer, and both of these two systems logged the system time and events used for data-preprocessing. After the reasoning task, a questionnaire was asked to fill out, including participants' basic information, their responses to reasoning test, and their self-assessment of confusion for each test.

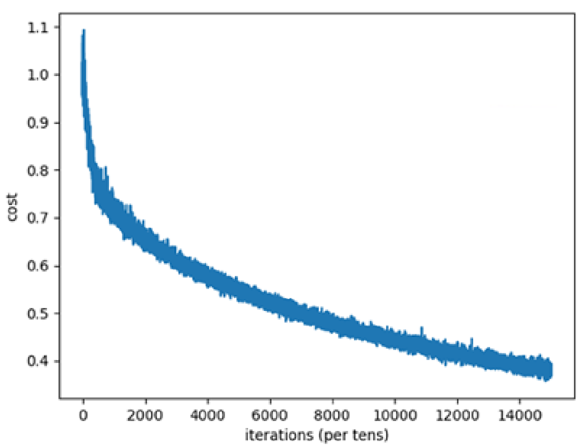

Fig. 5. The training loss.

D. Results and Discussion

We employed TensorFlow to build our end-to-end learning model for human confusion analysis. It was applied on the experiment environment is as follows: Operation System: Ubuntu 17.10, Graphics Card: GeForce GTX 970 and Memory: 15.6 GB. The input data is from the raw EEG data obtaining from 16 subjects as stated above. Each subject has been tested by 40 independent test questions, including confusing and not-confusing picture questions. In total, 640 (16×40) pieces of data were used for building and testing the classifier. We randomly chose 30% of samples as the test set. The rest of samples, namely, 70% of samples were training test. Learning rate is set as 0.00001, and the Adam [15] is set as the optimizer. The training loss is presented as shown in Figure 5. According to the training, our method can get the accuracy of 71.36% by only taking from the raw EEG data, which achieves our expectations.

IV. Conclusion and Future Work

This study is motivated due to missing studies on the triggering and detecting confusion in learning environment. In this preliminary work, we design and propose a system to classify the confused state and unconfused state using EEG-based wireless headset Emotiv Epoc+. The current system is able to record EEG signals and classify levels of confusion with an accuracy of 71.36% when individuals doing reasoning tests. Based on the dynamics of learning affect model revolving around confusion, when the level of confusion reaches a high level, the frustration and boredom will occur. Therefore, in our near future work, we will investigate a fine-grained multilevel confusion induction and classification, which will be applied in the digital learning system.

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