

Using EEG to Improve Massive Open Online Courses Feedback Interaction

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Abstract. Unlike classroom education, immediate feedback from the student is less accessible in Massive Open Online Courses (MOOC). A new type of sensor for detecting students' mental states is a single-channel EEG headset simple enough to use in MOOC. Using its signal from adults watching MOOC video clips in a pilot study, we trained and tested classifiers to detect when the student is confused while watching the course material. We found weak but above-chance performance for using EEG to distinguish when a student is confused or not. The classifier has a comparable performance to human observers observing body language in predicting students' confusion. This pilot study shows promise for MOOC-deployable EEG devices being able to capture tutor relevant information.

Keywords: MOOC, EEG, confuse, feedback, machine learning

1 Introduction

In recent years, there is an increasing trend towards the use of Massive Open Online Courses (MOOC), and it is likely to continue [1]. MOOC can serve millions of students at the same time, but it also has its own shortcomings. In [2], Thompson has explored the attitudes of post-secondary students who were negatively disposed toward correspondence-based distance education programs. Their results indicate that feedback and interaction are two problems of long-distance education. Current MOOC can offer interactive forums and feedback quizzes to help improve the communication between students and professors, but the impact of the absence of a classroom is still under heated discussion. [3] indicates lacking feedback if one of the main problems for students-teachers long distance communication.

There are many gaps between online education and in-class education [4] and we will focus on one of them: detecting students' confusion level. Unlike in-class education, where a teacher can judge if the students understand the materials by verbal inquiries or their body language (e.g., furrowed brow, head scratching, etc.), immediate feedback from the student is less accessible in long distance education. We address this limitation by using electroencephalography (EEG) input from a commercially available device as evidence of students' mental states.

The EEG signal is a voltage signal that can be measured on the surface of the scalp, arising from large areas of coordinated neural activity manifested as synchronization (groups of neurons firing at the same rate) [3]. This neural activity varies as a function of development, mental state, and cognitive activity, and the EEG signal can measurably detect such variation. Rhythmic fluctuations in the EEG signal occur within several particular frequency bands, and the relative level of activity within each frequency band has been associated with brain states such as focused attentional processing, engagement, and frustration [4-6], which in turn are important for and predictive of learning [7].

The recent availability of simple, low-cost, portable EEG monitoring devices now makes it feasible to take this technology from the lab into schools. The NeuroSky “MindSet,” for example, is an audio headset equipped with a single-channel EEG sensor [8]. It measures the voltage between an electrode that rests on the forehead and electrodes in contact with the ear. Unlike the multi-channel electrode nets worn in labs, the sensor requires no gel or saline for recording and therefore requires much less expertise to position. Even with the limitations of recording from only a single sensor and working with untrained users, a previous study [9] found that the MindSet distinguished two fairly similar mental states (neutral and attentive) with 86% accuracy. MindSet has been used to detect reading difficulty [10] and human emotional responses [11] in the domain of intelligent tutoring systems.

A single-channel EEG device headset currently costs around \$99-149 USD, which is a cost added on to the free service of MOOC. We propose that MOOC providers (e.g. Coursera, edX) supply an EEG device for students. In return, MOOC providers would get feedback on students EEG brain activity or confusion level while students watch their course materials. These objective EEG brain activities can be aggregated and augment subjective rating of course materials to provide a simulation of real world classroom responses, where a teacher is given feedback from an entire class. Then teachers can improve video clips based on these impressions. Moreover, even though EEG device is a luxury device at the moment, the increasing popularity of consumer-friendly EEG devices may one day makes it a house-hold accessory just like audio headset, keyboard and mouse. Thus, we are hopeful to see our proposed solution to be applicable as the market of MOOC grows and the importance of course quality and student feedback rises.

To assess the feasibility of collecting useful information about cognitive processing and mental states using a portable EEG monitoring device, we conducted a pilot study. We wanted to know if EEG data can help distinguishing among mental states relevant to confusion. If we can do so better than chance, then there is a “there there” – i.e., these data contain relevant information that future work may decode more accurately. Thus we address two questions:

1. Can EEG detect confusion?
2. Can EEG detect confusion better than human observers?

The rest of this paper is organized as follows. Section 2 describes the experiment design. Section 3 and 4 answers the two research questions, respectively. Finally, Section 5 concludes and suggests future work.

2 Experiment Design

In a pilot study, we collected EEG signal data of college students while they watched MOOC video clips. We extracted online education videos that are assumed to be not confusing for a college student, like videos of introduction of basic algebra or geometry. We also prepare videos that are assumed to confuse a normal college student if a student is not familiar with the video topics like Quantum Mechanics, Stem Cell Research¹. We prepared 20 videos, 10 in each category. Each video was about 2 minutes. We chopped the two-minute clip in the middle of a topic to make the videos more confusing.

We collect data from 10 students. One student was removed because of missing data due to technical difficulty. An experiment with a student consisted of 10 sessions. We randomly picked five videos of each category and randomized the presentation sequence so that the student could not guess the predefined confusion level. In each session, the student was first instructed to relax their mind for 30 seconds. Then, a video clip was shown to the student where he/she was instructed to try to learn as much as possible from the video. After each session, the student rated his/her confusion level on a scale of 1-7, where 1 corresponded to the least confusing and 7 corresponded to the most confusing. Additionally, there were three student observers watching the body-language of the student. Each observer rated the confusion level of the student in each session on a scale of 1-7. The conventional scale of 1-7 was used. Four observers were asked to observe 1-8 students each, so that there were not an effect of observers just studying one student.

The students wore a wireless single-channel MindSet that measured activity over the frontal lobe. The MindSet measures the voltage between an electrode resting on the forehead and two electrodes (one ground and one reference) each in contact with an ear. More precisely, the position on the forehead is Fp₁ (somewhere between left eye brow and the hairline), as defined by the International 10-20 system [12]. We used NeuroSky's API to collect the following signal streams:

1. The raw EEG signal, sampled at 512 Hz
2. An indicator of signal quality, reported at 1 Hz
3. MindSet's proprietary "attention" and "meditation" signals said to measure the user's level of mental focus and calmness, reported at 1 Hz
4. A power spectrum, reported at 8 Hz, clustered into the standard named frequency bands: delta (1-3Hz), theta (4-7 Hz), alpha (8-11 Hz), beta (12-29 Hz), and gamma (30-100 Hz).

¹ <http://open.163.com/>

3 Can EEG detect confusion?

3.1 Training classifiers

We trained Gaussian Naïve Bayes classifiers to estimate, based on EEG data, the probability that a given session was confusing rather than not confusing. We chose this method (rather than, say, logistic regression) because it is generally best for problems with sparse (and noisy) training data [13].

We use two ways to label the mental states we wish to predict. One way is the *pre-defined* confusion level according to the experiment design. Another way is the *user-defined* confusion level according to each user’s subjective rating.

The EEG device emits the various signals enumerated earlier, while the students watch the 2 minutes video. In case a student was not ready when the video started, we removed the leading 30 seconds and final 30 seconds of that video and only analyzed the EEG signal in the middle 60 seconds. To characterize their overall values, we computed their means over the interval of each utterance. To characterize the temporal profile of the EEG signal, we computed several features, some of them typically used to measure the shape of statistical distributions rather than of time series: minimum, maximum, variance, skewness, and kurtosis. However, due to the small number of data points (100 data points for 10 subjects, each watching 10 videos), inclusion of those features tends to overfit the training data and result in poor classifier performance. As a result, we simply use the means as the classifier features. We did not search intensively for features because feature selection is not the focus of this work. **Table 1** shows the classifier features.

Table 1. Classifier features

Features	Sampling rate	Statistic
Attention (proprietary)	1 Hz	Mean
Meditation (proprietary)	1 Hz	Mean
Raw EEG signals	512 Hz	Mean
Delta frequency band	8 Hz	Mean
Theta frequency band	8 Hz	Mean
Alpha1 frequency band	8 Hz	Mean
Alpha 2 frequency band	8 Hz	Mean
Beta1 frequency band	8 Hz	Mean
Beta 2 frequency band	8 Hz	Mean
Gamma1 frequency band	8 Hz	Mean
Gamma2 frequency band	8 Hz	Mean

To avoid overfitting, we used cross validation to evaluate classifier performance. We trained *student-specific* classifiers on a single student’s data from all but one stimulus block (e.g. one video), tested on the held-out block (e.g., all other videos), performed this procedure for each block, and averaged the results to cross-validate accuracy within reader. We trained *student-independent* classifiers on the data from

all but one student, tested on the held-out student, performed this procedure for each student, and averaged the resulting accuracies to cross-validate across students.

3.2 Detect pre-defined confusion level

We trained and tested classifiers for pre-defined confusion. Average accuracies of student-specific and student-independent classifiers were 67% and 57%, respectively. Both classifier performances were statistically significant better than a chance level of 0.5 ($p < 0.05$). **Fig. 1** plots the classifier accuracy for each student. White bars indicate the accuracy of student-specific classifiers and black bars indicate the accuracy of student-independent classifiers. **Fig. 1** shows that both student-specific classifiers and student-independent classifiers performed significantly above chance in 6 out of 9 students.

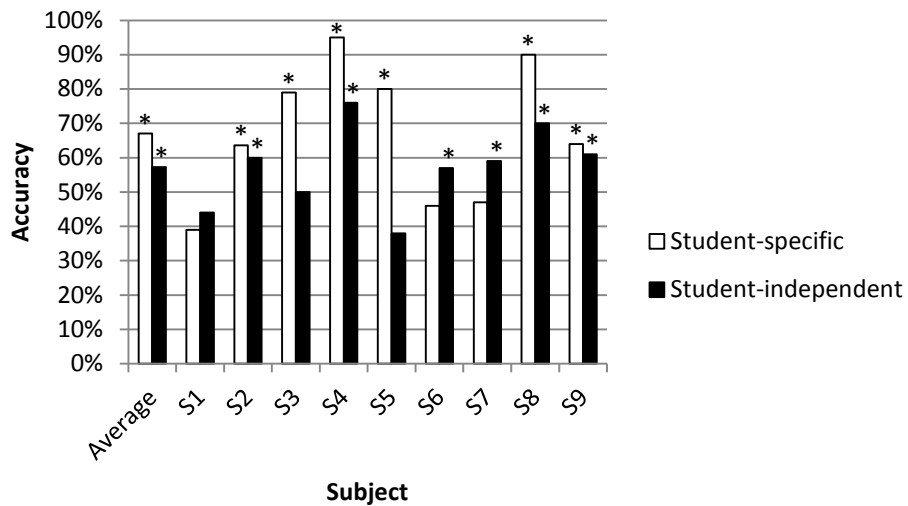


Fig. 1. Detect predefined confusion level

3.3 Detect user-defined confusion level

We also trained and tested classifiers for student-defined confusion. Since students have different sense of confusing, we mapped the seven scale self-rated confusion level into a binary label, with roughly equal number of cases in the two classes. A middle split is accomplished by mapping scores less than or equal to the median to “not confusing” and the scores greater than the median are mapped to “confusing”. Furthermore, we used random undersampling of the larger class(es) to balance the classes in the training data. We performed the sampling 10 times to limit the influence of particularly good or bad runs and obtain a stable measure of classifier performance.

Average accuracies of student-specific and student-independent classifiers were 56% and 51%, respectively. The student-specific classifier performance was statisti-

cally significant better than a chance level of 0.5 ($p < 0.05$), but not the student-independent classifier. **Fig. 2** plots the accuracy for each student. **Fig. 2** shows that student-specific classifier performed significantly above chance in 5 out of 9 students and student-independent classifier performed significantly above chance in 1 out of 9 students.

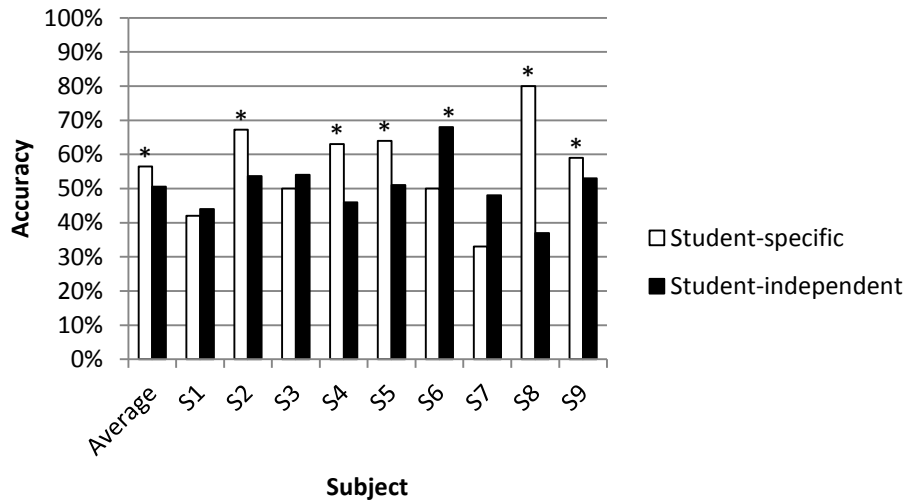


Fig. 2. Detect user-defined confusion level

4 Can EEG detect confusion better than human observers?

To determine if EEG can detect confusion better than human observers based on body language can, we compared the scores from the observer, the classifier, students' own score and the label of videos. For each session of each student, we took the average score of observers as the 'observer rating'. We used the classifier trained in Section 3 to predict predefined confusion level and linearly mapped the classifier's estimate of class probability (0-100%) to a scale of 1-7 and labeled it as the 'classifier rating'.

The score of classifier has a low, but positive correlation (0.17) with students' own score, while the score of observer has a low, but positive correlation of (0.17) with students' own score. This shows that classifier has comparable performance to human observers observing body language in predicting students' confusion.

5 Conclusions and Future Work

In this paper, we described a pilot study, where we collected students' EEG brain activity while they learn from MOOC video clips. We trained and tested classifiers to detect when a student was confused. We found weak but above-chance performance for using EEG to distinguish whether a student is confused. classifier has comparable

performance to human observers observing body language in predicting students' confusion.

Since the experiment was based on a project run by a group of graduate students, there were many limitations to the experiment. We now discuss the major limitations and how we plan to address them in the future work.

One of the most critical limitations is the definition of experimental construct. Specifically, our pre-assigned "confusing" videos could be confounded. For example, a student may not find a video clip on Stem Cell to be confusing when the instructor clearly explains the topic. Also, the predefined confusion level may be confounded with increased mental effort / concentration. To explore this issue, we examined the relationship between the predefined confusion level and the subjective user-defined confusion level. The students' subjective evaluation of the confusion level and our predefined label has a modest correlation of 0.30. Moreover, we performed a feature selection experiment among all combinations of 11 features; we used cross validation through all the experiments and sorted the combinations according to accuracy. Then we found that the user specific model THETA signal played an important role in all the leading combinations. THETA signal corresponds to errors, correct responses and feedback, suggesting what we are classifying is indeed confusion.

Another limitation is due to the lack of psychological professionalism. For example, the observers in our experiment were not formally trained. As a result, the current scheme allowed each observer to interpret a student's confusion level based on his/her own observations. A precise labeling scheme would yield more details that could be compared among raters. We would like to improve our procedure for having observers rate a student's confusion level.

Another limitation is the scale of our experiment as we only performed the experiments with 10 students, each student only watched 10 2-minute video. The limited amount of data points prevents us from drawing any strong claim about the study. We hope to scale up the experiment and collect more data.

Finally, this pilot study shows positive, but weak classifier performance in detecting confusion. The weak classifier performance may frustrate a student. Moreover, a student may not be willing to share their brain activity data due to privacy concerns. With that said, we are hopeful that the classifier accuracy can be improved once we conduct a more rigorous experiment, increasing the study size, and improve the classifier (e.g. better feature selection method and applying denoising techniques to improve signal-to-noise ratio, etc.). Also, the classifiers are supposed to help the students and the students can choose not to use EEG if they think the device is hindering.

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