Analysis of Brainwave (EEG) Signals for Confusion

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ABSTRACT

MOOC - Massive Open Online course don't support immediate feedback from students like Live classroom education. A new type of sensor has been used to detect the mental state of the students. This sensor is a single channel EEG headset which is quite simple to be used in MOOC. In this pilot study, the researchers have trained and tested classifiers in order to detect whether the student is confused while watching the video of the course material.

There existed a weak yet above chance performance in the usage of the EEG in order to classify whether the student is confused or not. There were human observers who monitored and studied the student body language and rated confusion levels for each student. This study shows promise for Massive Open Online course to use EEG devices for being able to capture information related to student-tutor interaction.

1. INTRODUCTION

Massive Open Online Courses (MOOC) have widely evolved over the years. It serves huge masses of students, but at the same time has its own share of shortcoming. There was a study performed where students, who had a negative attitude about distance learning were studied. Some of the shortcomings were immediate feedback and personal interaction. Currently, some of the features of the MOOC's present today are forums, feedback quizzes which enhance the communication between the students and the professors. Yet, online education and live in class education have many uncovered gaps. This study stresses on detecting students' confusion level while watching a MOOC video.

Benefits of in-class education is when teacher can judge if a particular student can understand the material that is being taught by asking verbal inquiries or by studying their body language. Students can give immediate feedback to the teachers. In order to bridge the gap between online learning and in-class learning, EEG brainwaves of the student watching an online video are recorded and studied to detect if the student is finding the video to be confusing. Electroencephalography (EEG) input from a widely available device is an evidence of students' mental states. [7][8] The dataset contains these readings along with the student's feedback about the video (confusing or not). This data is used as the training data to classify new EEG brainwaves of a student watching a video. [6]

2. OTHER WORKS RELATED TO OUR STUDY

2.1 Using EEG to Improve Massive Open Online Courses Feedback Interaction – *Haohan Wang, Yiwei Li, Xiaobo Hu, Yucong Yang, Zhu Meng, Kai-min Chang - Language Technologies Institute, School of Computer Science, Carnegie Mellon University* [1]

2.1.1 Approach Used

EEG signal data was collected from college students while they watched Mass Open Online Courses (MOOC) video clips. Initially, an assumption made is that the online education videos were extracted, such as videos of geometry or basic algebra. In addition, there are videos which tend to confuse the students who aren't familiar with concepts like Stem Cell Research, and Quantum Mechanics were also prepared. 20 videos were prepared, 10 in each category and about 2 minutes long. The two-minute clips were chopped in the middle to make the videos more confusing. Data was collected from 10 students. An experiment with each student consisted of ten sessions. Five videos were randomly picked of each category and the presentation sequence was randomized to make sure that the predefined confusion level couldn't be guessed by a student. In each session, the students were first instructed to relax their mind for a period of 30 seconds. Following this, a video snippet was provided to the student where he/she was advised to pick up as much as possible from the video. Post each session, the students rated their level of confusion on a scale of 1-7, with 1 corresponding to the least confusing and 7 to the most confusing. The body language of the students was observed by 3 other student observers. Each other student observer rated the level of confusion of the students in each session on a similar scale of 1-7. Anywhere between 1 to 8 students were observed by 4 observers, so that there was no effect of observers just studying a single student. The students were given a wireless MindSet (single-channel) that was used to measure frontal lobe activity.

2.1.2 Summary of the results

Classifiers were trained and tested to detect the confusion levels of a student. Above-chance, yet weak performance was found for using EEG to detect the fact of a student, being confused or not. The classifier's performance was analogous to the human observers who monitored students' body language and accordingly evaluated the confusion levels of students. The relationship between the subjective user-defined and predefined confusion level was examined. The subjective evaluation of the confusion level of the students and their predefined label had a correlation of 0.30. Next, a feature selection experiment was performed among all combinations of 11 features; and cross validation was used through all experiments and the combinations were sorted according to accuracy. It was found that the Theta signal from the user-specific model played an important role in all the main combinations. The Theta signal corresponds to correct responses, errors and feedback, suggesting that the experimental construct is related to confusion. Finally, the pilot study shows a positive, but weak classifier performance in helping detect confusion. The weak classifier performance may also be vulnerable to false-alarms and can thereby frustrate a student.

2.1.3 Limitations

The definition of the experiment construct by itself is a critical limitation, which could prove to be a limitation in our analysis as well. A video which we define to be 'confusing' may not be confusing at all. If the instructor on a video explains a topic clearly, a student may not find it confusing. Also, fluctuations in mental effort/concentration could mislead predefined confusion levels. The experiment lacks psychological professionalism too. The observers of the experiment were not professionally trained to observe and study the body language of the subject. Hence, there is a possibility of error to have crept into the data. The scale of the experiment is also a limitation. Data obtained from 10 subjects watching ten 2-minute videos is too small a data to study and make inferences about.

2.2 Brainwave recognition of words - *Patrick Suppes, Zhong-Lin Lu and Bing Han - Proceedings of the National Academy of Sciences, United States of America* [2]

2.2.1 Outline

Under three different experimental conditions and conscious awareness of seven subjects, global electrical and magnetic brainwaves of the subjects were recorded. The recorded signals were used to recognize, which one of the seven test words was the subject processing at the time of recording. Certain filters were applied on the Fourier transform of the recorded data to enhance the results. The best results were obtained for 2 subjects, with a high recognition rate of ~90%.

2.2.2 Purpose of choosing the paper

This paper, in particular, is an important reference to us in many ways. The authors of the paper describe how they use data analytics to predict a word that is being processed by a subject using various values associated with the brainwave frequency band of his/her brainwave. Hence, this problem would unequivocally help us gain a better understanding of our problem. The paper provides an insight to how the initial dataset was scrubbed to obtain a clean dataset, how the data scientists performed their initial analysis to study interesting and possible patterns in the dataset and the various techniques used and implemented by the analysts to recognize the word processed by the subject. These intricacies will definitely serve as a guiding light to us, to go about our current problem.

2.2.3 Approach used

Seven subjects were subjected to different experimental conditions and each subject was asked to perform activities based on a word showed on the screen such as silently "say" the word shown on screen, read aloud the word shown on the screen thinking about it, etc. All subjects were recorded in auditory comprehension condition, while a few in internal speech condition. For every trial, the average of the observations before the onset of the stimulus was used as the baseline (204 observations recorded). To eliminate noise, this baseline was subtracted from each trial following which the data was averaged for every word for every alternate trial. A Fast-Fourier transform was applied on each observation. The result was filtered by applying an optimal bandpass filter (optimal to each subject) following which an inverse Fast-Fourier transform was applied on the transformed data. Minimum least-square was used as the criterion for evaluation of prediction.

2.2.4 Summary of the results

91% of the brainwave predictions for subject 1 in the internal speech condition were accurate. The prediction accuracy for the other subjects ranged from 34% to 90%. A subject-independent analysis was also performed on the processed dataset and the following results were obtained:

- In the condition of auditory comprehension, when S1 prototypes were used for the purpose of training, 16 S2 test samples (35) were classified (correctly reversed), the number was 11.
- In similar experimental condition, when training was performed using S3 prototypes, 11 test samples (S4) were correctly classified, and when reversed, 12 were correctly classified.
- When S1 prototypes were used for training, in the internal speech condition, 16 S2 samples were correctly classified, and when reversed, the number was 18.

2.2.5 Limitations

Though the best result that was obtained corresponded to 91%, the prediction accuracy ranged from 34% which indeed provides a huge scope for improvement. For auditory comprehension, the prediction accuracy ranged from 37% to 77% which is again a wide range to imply any conclusions. The prediction accuracies definitely need to be improved.

2.2.6 Lacuna in approach

Movies of the brain processing a particular word (spatiotemporal, continuously changing image of the brain) could be a potential source of additional concepts that may be required for accurate recognition of a word. Also, as stated earlier, the experiments were performed when the subject was consciously aware about processing a word. Tests need to be performed to verify the adequacy of this global level information to recognize words when the subject is not consciously aware of the same. This could require some additional data, which is found only in the inaccessible individual neurons which are the sources of these waves. This data could be difficult to obtain.

2.3 I Think, Therefore I Am: Usability and Security of Authentication Using Brainwaves - *John Chuang, Hamilton Nguyen, Charles Wang, Benjamin Johnson - School of Information, Department of EECS, Department of Mathematics, UC Berkeley* [3]

2.3.1 Outline

The growing availability of EEG technology, a research agenda is used for development and evaluation of many practical methods for general regular users so that they can apply their own brainwave data, in everyday settings, for different computer-based applications. They have taken the first step by placing their focus of the problem on the authentication of the user by using brainwaves. They evaluated users performing different classes of mental tasks while wearing the headset. EEG data from human subjects, experiments and several questionnaires of data, in order to measure the level of usability of these tasks, were also collected.

- The 1st main finding is, single channel EEG signals exhibit patterns that are specific to the subject. A higher similarity between within the subjects was found than across the subjects.
- The 2nd key discovery is that EEG single channel authentication can almost be as accurate as multi-channel EEG authentication. They evaluated a collection of threshold-based protocols for authentication that accepts or rejects decisions. Using custom tasks and thresholds for each user, they reduced false error rates down to the 1% level.
- Their 3rd discovery is that neither the signal similarity nor the performance of authentication are affected significantly by the categories of mental tasks done by the subjects. Personalized mental tasks do not produce higher signal similarity or higher authentication accuracy over common mental tasks to all subjects.
- Their 4th key finding is that different categories of mental tasks are scored very differently based on user perceived enjoyability and difficulty. Different subjects assign different weights to enjoyability and to the difficulty in making their choice.

2.3.2 Approach used

The research that they conducted based on the experiment involved human based subjects, and their experimental procedures were approved and reviewed by the Institutional Review Board. Each subject met up with two investigators in an enclosed room for two 40-50 minute sessions on different days. The subjects were fitted with a headset called the “Neurosky MindSet”, and provided the human subjects with instructions for completing each of 7 tasks. As the subjects performed each task the researchers monitored and recorded their brainwave signals.

Tasks that were performed by the subjects and repeated 5 times:

- Breathing Task (breathing) Subjects
- Simulated Finger Movement (finger) Subjects
- Sports Task (sport) Subjects
- Song/Passage Recitation Task (song) Subjects
- Eye and Audio Tone Task (audio) Subjects
- Object Counting Task (colour)
- Pass thought Task (pass) Subjects

2.3.3 Summary of the results

The performance and the usability of brainwave based authentication was studied. The inspiration of the trend of budget EEG sensors embedded in various electronic devices, they have conducted an experimental study to capture brainwave signals from subjects using consumer friendly EEG headsets in an environment deemed to be non-clinical. They designed several mental tasks for the human subjects to perform. Evaluation of the utility of tasks based on difficulty, enjoyability and repeatability is done.

Finding: Brainwave signals, including the budget EEG sensors (nonintrusive) in daily settings can be used in order to authenticate users with a considerable degree of accuracy.

They can bypass the challenges of usability associated with conventional EEG systems specifically designed for clinical applications. Different tasks differ in their usability. Subjects will tend not to opt for repeating difficult or boring tasks. Similar to the experience with graphical passwords, it is found that past thoughts picked by subjects can be recalled without much difficulty. In comparing the results of the authentication testing with that of usability analysis, it is observed that it is unnecessary to sacrifice utility and usability for accuracy. It is possible to achieve accurate authentication with enjoyable and easy tasks.

2.4 Classification of EEG Signals from Four Subjects During Five Mental Tasks - *Charles W. Anderson and Zlatko Sijerčić, Department of Computer Science, Colorado State University* [4]

2.4.1 Outline

The neural networks are initially trained to classify six-channel segments in intervals of half seconds, EEG data into a single class out of five classes corresponding to a set of five cognitive tasks performed by a total of four subjects. Two or three-layer neural networks (feedforward) are trained using the method of 10-fold cross-validation and prematurely stopped to limit overfitting. EEG signals were represented by a set of autoregressive (AR) models. The percentage average of test segments was correctly classified and varied from 38% in one subject and 71% for another subject. The unit weight vectors are quite subjective for the resulting neural networks on which cluster analysis needs to be done and finds out which EEG channels are closely related and relevant with respect to this problem of discrimination.

2.4.2 Purpose of choosing the paper

The paper in question helps in gaining an insight into EEG analysis with respect to the 4 frequency bands (Delta, Theta, Alpha and Beta) and is in line with our proposed model of work which also aims to classify EEG data from a select band of subjects into distinct classes based on their state of mental confusion. It also serves as a guide in ironing out such imperfections to enable deliverance of a sustainable data model.

2.4.3 Approach used

The data from four subjects performing a set of five mental tasks was subjected to analysis. These tasks were chosen so as to invoke hemispheric brainwave asymmetry. The five tasks are: the baseline task, where the subjects were advised to completely relax; the letter task, for which the subjects were asked to mentally compose a letter to a relative or friend without any sort of vocalising; the math task, for which the subjects were provided a set of nontrivial arithmetic problems, such as 63 times 97, and were asked to solve them again without any sort of physical movement; the visual counting task, where the subjects were asked to visualise a blackboard and numbers being written on the board sequentially along with rotation of a geometric shape, and the participants were made to visualize a specific three-dimensional block figure which is rotated about a central line namely the axis. With a sampling rate of 250Hz, each ten second trial produces a set of 2,500 samples per channel. The best classification results were obtained using a Fourier Transform algorithm based on AR-coefficients. Coefficients that minimise the squared error of the prediction were estimated using an algorithm called Burg method. The classifier used is a feedforward, standard, neural network with 1-2 hidden layers and 1 output layer, trained with an error back-propagation algorithm.

2.4.4 Summary of the results

A RMS error of 0.5 is initially obtained and the training error keeps decreasing all through the training period but a clear minimum occurs on the validation error. The classification and error performance on the test set is computed at that point as an indication of how well the network generalises to novel data. For the test segments which were correctly classified, the average percentage varied from 38 percent for one subject to 71 percent for another subject. The best average performance achieved with such a model is where 54% of the segments are classified correctly.

2.4.5 Limitations

The prediction accuracy spans from 38% all the way to 71% across subjects. Such anomalies may be attributed to the fact that the data used corresponds to overlapping half-second segments of time. This may give rise to anomalous errors creeping in at every stage of analysis. Another potential pitfall may be attributed to the difficulty of each task assigned to the subjects. For example, in the math task, one subject may have received a relatively easy problem as opposed to someone else.

2.4.6 Lacuna in approach

It must be ensured that all subjects are judged based on mentally similar problems in order to provide an accurate analysis by equally distributing each level of the five tasks among the subjects. Also, care must be taken to ensure that the data collected is distinct and not overlapping to prevent any errors from bubbling across stages.

2.5 Toward Exploiting EEG Input in a Reading Tutor - *Jack Mostow, Kai-min Chang, and Jessica Nelson - Project LISTEN, School of Computer Science, Carnegie Mellon University, USA* [5]

2.5.1 Abstract

Using signals of a single channel EEG headset from subjects who were made to read text and individual words, both audibly and silently, classifiers were trained and tested to distinguish easy and hard sentences, and to differentiate between easy, hard and pseudo-words, and unpronounceable words.

2.5.2 Purpose of choosing the paper

This paper has a similar qualitative pattern to the current problem at hand. The statistically dependable relationship between reading difficulty and EEG data is clearly demonstrated in this paper and this approach would assist us to detect mental states. This information can help us generate and test various hypotheses about learning, emotion, cognition, and any other required behaviour.

2.5.3 Approach used

15 readers which included 6 adults and 9 children participated in the lab. A reading tutor displayed text, listened to the subject read aloud, and logged EEG signal data to a database. Binary logistic regression classifiers were trained to estimate the probability that a given sentence was easy (or hard), based on EEG data. Separate classifiers were trained for each condition (oral and silent reading) and group (adults and children). Reader-specific classifiers were trained on a single reader’s data from all but one passage or word, and were tested on the held-out stimulus, this procedure was performed for each stimulus, and mean of the results was used to verify accuracy among readers. Reader-independent classifiers were trained on the

data from all but one reader, tested on the held-out reader, this procedure was performed for each reader, and resulting accuracies were averaged to cross-validate across readers.

2.5.4 Summary of the results

There were no significant differences between children's and adults' data, but word and sentence reading varied sharply, as did silent and oral reading. Classifiers were trained to distinguish between hard and easy sentences read silently, aloud, or both, by children, adults, or both. Determined by the resampling method used, accuracy varied from 43% to 69% for reader-specific classifiers while the accuracy varied from 41% to 65% for reader-independent classifiers. Reader-specific classification of children's oral reading was specifically good, which holds good for detecting reading struggles in the reading tutor.

2.5.5 Limitations

One limitation in training classifiers is class size imbalance. This issue is faced as there are more number of easy sentences than there are hard ones and more non-words than real words. The training data can be resampled to obtain equal-size sets of training data. However, random under sampling could potentially remove some important examples, and random oversampling could lead to overfitting. This class size imbalance creates bias.

2.5.6 Lacuna in approach

Additional mental states need to be detected. Classifier accuracy must be improved by collecting more data and by using more sophisticated training methods. Besides manipulating stimuli experimentally, training data can be labelled based on observable events in longitudinal EEG data, such as improved performance.

3. PROBLEM STATEMENT

EEG brainwave for confusion - Using EEG brain activity data to predict if a video is confusing to a student or not.

Variable 'student-defined confusion level' is the target variable. We use other variables in the dataset to predict this variable. We intend to better the accuracy of prediction already obtained by authors of paper '*Using EEG to Improve Massive Open Online Courses Feedback Interaction, Carnegie Mellon University*'[1] using a number of techniques that have not yet been tested on this dataset.

4. APPROACH

As mentioned in the Section 2.1.1, researchers have used Gaussian Naïve Bayes classifiers to build a classifier to classify a given session as confusing or not confusing based on the probability calculated. This does not work really well for large and noisy datasets. The dataset we are dealing with is exceedingly sparse and prone to noise due to the effect of external factors on the mental conditions of the subject at the time of recording the readings. Alternatively, we are trying out a number other techniques to classify a recording and hence, increase the percentage of accuracy of classification. These techniques include, C4.5 algorithm, Support Vector Machines, Fourier Transform algorithm, decision trees, random forests, etc. Bagging may be performed on the output of these algorithms to classify a particular reading and infer if the subject found it confusing or not.

CITATIONS

[1] Haohan Wang, Yiwei Li, Xiaobo Hu, Yucong Yang, Zhu Meng, Kai-min Chang "Using EEG to Improve Massive Open Online Courses Feedback Interaction" Language Technologies Institute, School of Computer Science, Carnegie Mellon University

[2] Patrick Suppes, Zhong-Lin Lu, And Bing Han "Brain wave recognition of words" Center for the Study of Language and Information, Stanford University, Stanford, CA 94305; and Department of Psychology, University of Southern California, Los Angeles, CA 90089

[3] John Chuang, Hamilton Nguyen, Charles Wang, and Benjamin Johnson "I Think, Therefore I Am: Usability and Security of Authentication Using Brainwaves" School of Information, UC Berkeley Department of EECS, UC Berkeley Department of Mathematics, UC Berkeley

[4] Charles W. Anderson and Zlatko Sijercic "Classification of EEG Signals from Four Subjects During Five Mental Tasks" Department of Computer Science Colorado State University Fort Collins, CO 80523

[5] Jack Mostow, Kai-min Chang, and Jessica Nelson "Toward Exploiting EEG Input in a Reading Tutor" Project LISTEN, School of Computer Science, RI-NSH 4103, 5000 Forbes Avenue, Carnegie Mellon University, Pittsburgh, PA 15213, USA

[6] Haohan Wang "EEG brain wave for confusion detection" Kaggle

[7] WIKI "Electroencephalography"

[8] What are Brainwaves? | brainworks "http://www.brainworksneurotherapy.com/what-are-brainwaves"

[1] Paper 1 in Section 2, 'Other Works related to our Study'