Brain-Computer Interface Enhanced Adaptive Learning

Initial Electroencephalograph Trials

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***Abstract*—Adaptive Learning educational systems are a modern solution to the problem of limited manpower in education. Although they are capable of various types of adaptation, one type which they lack is the ability to adapt to student emotional responses. In an effort to remedy this, we have attempted to incorporate a brain-computer interface into the system in the form of an electroencephalograph. Data was collected in a quiz-type interface, and fed into a prediction algorithm in order to simulate software adaptation. Initial trials showed that much more student trials are needed, but the research up to this point is sound as a preliminary approach. Until this project achieves board approval, true human testing cannot commence. The present status of this project is postponed temporarily.**

Keywords—EEG, Electroencephalograph, Education, Adaptive Learning, Machine Learning, NSF Grant, REU Program, East Carolina University

I. INTRODUCTION

In the field of Education, Adaptive Learning refers to technology systems designed to educate or tutor students by adapting to their individual needs and interests. Modern Adaptive Learning implementations diversify based on what parameters they adapt to. As a rule, any system of any complexity can only adapt to information passed into the computer system through some means or another. Another technology, Electroencephalography, refers to the study of the electromagnetic activity produced by brain activity. In recent commercial development, this technology is finding its way into the consumer sector as a new interface device for computers. Modern Adaptive Learning technology has no access to the student's thoughts and feelings. Electroencephalography(EEG) has limited access to these parameters, and by combining Adaptive Learning systems with an electroencephalographic interface, Adaptive Learning technology can be improved.

Adaptive learning technology will always be less effective in most cases than interpersonal tutoring as long as there is no access to the student's thoughts and feelings. A human tutor can see when a student is frustrated or guessing, or is otherwise emotionally affected. By giving adaptive learning systems access to this information, it is possible that adaptive learning systems will cease to be a supplement for instruction, and begin to be a primary method. Education is always at a premium, and every person has different interests and needs. While there are some things that are agreed upon as necessary parts of education, the individual needs of every student are not met. This creates a rift between the desired effect and the achieved result. In order to produce truly and completely educated adults, every person would need to have his or her own individual tutor. There is no support for such a system through conventional means. However, if that individual tutor were artificial, support would be much easier to find.

This experiment attempts to address this issue by combining the technology of a commercially available electroencephalographic headset with a rudimentary scholastic computer interface. Our approach is to examine the question of "Can EEG technology improve adaptive learning systems?" by splitting it into two questions: "Can commercially available EEG technology provide an effective interface between a computer and a student's emotional and intellectual activity in an academic context?" and "Can information about students' emotional and intellectual activity improve the effectiveness of Adaptive Learning systems?" The reason for this is to create a context that is experimentally testable. We address the first of these questions experimentally, and assume the answer of yes to the second.

This paper is organized as follows: Section II describes the state of the art and related works, Section III describes the methodology and materials we used in our experiment, Section IV-a describes our results, Section IV-b describes our analysis, and Section V describes our conclusions and a summary.

II. RELATED WORKS

A. Adaptive Learning and EEG

There are very few other studies in place that incorporate Adaptive Learning and EEG technologies together. One such study being conducted at Leipzig follows a slightly different path than this project. The Leipzig approach is focused on measuring cognitive load during scholastic interactions, which is different from our study as we are measuring cognition levels as well as excitation levels. [2]

B. Adaptive Learning

In recent years, Adaptive Learning technology has become a popular trend in the business of education. McGraw-Hill, a name well known to any student or educator, has released a

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system called “LearnSmart,” which monitors many different variables of student interaction. One method which is characteristic of “LearnSmart” is that it attempts to analyze a student’s ‘metacognition’ in order to report on a student’s ability to monitor his or her own learning. “LearnSmart” primarily provides an interface for educators to develop supporting curriculum material and monitor student performance and ability on assignments delivered via the computer interface. It does not act as a direct instruction method. [6]

Another popular company in the Adaptive Learning field is a company called Cogbooks. Cogbooks’ methodology is uncommon in that they follow what they refer to as the granular approach. The software involved monitors and accounts for as much data as possible, and attempts to adapt to everything accordingly. This approach is beneficial in that it may provide a more effective adaptation to a student’s needs. This approach also carries the caveat of too much data, which is that any false measurement can create significant error. [5]

III. METHODOLOGY

The principle of the experiment is to compare the effectiveness of an Adaptive Learning software system with and without access to otherwise human-only accessible information about the user’s mental state. Ideally, this experiment would have used an advanced brain-computer interface with capability similar to that of a functional Magnetic Resonance Imager. Due to budget constraints and limits on availability of experts, we instead used a commercially available electroencephalograph (EEG) to create a somewhat more rudimentary interface. The EEG device employed in the course of this research is the Emotiv EPOC headset. This headset is designed to measure Cognition, Excitation, and Meditation. For the purposes of our experiment, we used only Cognition and Excitation. Because it is beyond the scope of this experiment, we did not employ extensive analysis of subject brain activity. The software employed is the basic version of the Emotiv SDK along with the EmoKey utility. We calibrated the EmoKey utility to provide feedback when the measured levels of Cognition and Excitation passed numerical barriers (0.2, 0.35, 0.5, 0.65, 0.8) either rising or falling.

We also did not incorporate a specific adaptive learning system, but rather a simple quiz-survey interface. This interface is limited to 23 simple multiple choice questions of various types. Using Dr. Leslie Wilson’s [1] five basic types of questions (Factual, Convergent, Divergent, Evaluative, and Combination) with at least one of each type for each of four major academic subjects (Mathematics, Science, Literature, and History) as well as three diagnostic survey questions regarding the subject’s preference of the subjects and opinion of the difficulty level of the questions.

A. Calibration and Testing Phase

During the initial implementation of the headset, we had set the EmoKey utility to register only above .75 and below .6. These numbers were sufficient in our first trial. Our first tests with other subjects demonstrated that these numbers were not sufficient for all subjects. As shown in table 1, our initial method of testing high and low levels around a specific baseline experienced precision error. We corrected for this by instead using a set of points to register at various resolution, showing whether the levels are rising or falling past certain numbers. For both cognition levels and excitation levels, we registered points at 0.2, 0.35, 0.5, 0.65, and 0.8. The second implementation produced sufficient resolution to record data.

Calibration Tests				
	Baseline	Minimum	Maximum	Range
Subject 1	0.7	0.4	0.8	0.3
Subject 2	0.5	0.3	0.7	0.4
Subject 3	0.8	0.95	0.75	0.2

Trials Phase

After initial calibration was completed, we tested 14 individuals of various ages, ethnicities, and backgrounds. In an effort to test the system we had created, we used their data to attempt to generate test cases. Apart from EEG data, the parameters involved are reaction time in milliseconds, correctness, and the subject’s actual preference for subject matter.

IV. PROPOSED ANALYSIS

The data recorded in this experiment is to be analyzed using two decision trees. One generated using all the available parameters as an experimental value, and one generated using only the parameters available to a conventional system. These decision trees will be generated using a C4.5 algorithm. The decision tree generation was chosen as a method of simulating the adaptation of an adaptive learning educational system. We did not use an actual adaptive learning educational system due to the scope of this experiment and the limited budget.

The two decision trees will be compared to determine the effectiveness of predicting a student’s interest in a given question. The initial 14 tests used for further calibration were run through this algorithm. The resulting prediction trees were slightly different, but suggest that more definitive results can be achieved by testing more subjects.

V. FUTURE WORK

The most important issue that this project faces at the moment is IRB approval. Our study has so far been reviewed twice and requires further alteration before it can be approved. Until such time as its approval, we cannot collect any data from human trials except for calibration and testing information that will not actually be published or used to support any theory or hypothesis.

The proposal put to the IRB is as follows:

The purpose of this research is to determine whether Adaptive Learning (Educational) software can be successfully augmented using a wireless EEG headset to test the engagement of the student to verify the effectiveness of the curriculum and instruction methods.

The subjects required will be a random sampling of 100 college students of varying background and education level (n=100 +/-10). The trials will consist of a subject wearing the headset while interacting with the software. The software will respond to the subject's interactions through the software *interface, as well as the subject's EEG responses in an effort to keep the curriculum and instruction methods engaging.*

Upon completion of the IRB approval process, this research will continue in the context of an ongoing project, hopefully collecting hundreds of student responses in order to generalize the prediction algorithm sufficiently to predict individual responses. We intend to continue this research in the fall of 2013, and possibly continue into the spring. By that time, we may have a solution.

We also intend to devise a better method of surveying questions. This will require nothing more than further development of the question interface, and altering the quiz information slightly.

VI. CONCLUSIONS

This project has been very difficult and frustrating. We have experienced a number of setbacks and challenges in the course of our work. I have personally learned a great deal about the research process and the methods involved in developing a thesis and following it through. I intend to continue this research until such time as it merits publication in a respected journal. But until that time, I will continue to collect data and refine the project.

V. REFERENCES

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