

Detecting Guessed and Random Learners' Answers through Their Brainwaves

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Abstract. This paper describes an experiment in which we tried to predict the learner's answers from his brainwaves. We discuss the efficiency to enrich the learner model with some electrical brain metrics to obtain some important information about the learner during a test. We conducted an experiment to reach three objectives: the first one is to record the learner brainwaves and his answers to the test questions; the second is to use machine learning techniques to predict guessed and random answers from the learner brainwaves; the third is to implement an agent that transmits the prediction results to an Intelligent Tutoring System. 21 participants were recruited, 45827 recordings were collected and we reached a prediction accuracy of 96%.

Keywords: Intelligent Tutoring System, Brainwaves, Learning, Guess.

1 Introduction

“when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind; it may be the beginning of knowledge, but you have scarcely in your thoughts advanced to the state of Science” Lord Kelvin

Using precise measures to get information from the learner state is a key point in improving the learner model within an Intelligent Tutoring System (ITS). The learner model is an important component within an Intelligent Tutoring System (ITS). By defining efficient metrics related to the learner behavior, an ITS increases its ability to adapt the material to the learner. Many researches in the field of Artificial Intelligence and Cognitive Sciences have contributed to the evolution of the learner model and the tutorial strategies. Thus, to the cognitive model [15] were added other layers like the psychological model [5], the affective model [10] and the motivational model [3] with specific tutorial strategies. To get information about the learner, data collection methods have also evolved from self report [2] to facial expression analysis [13], posture and gestures interpretations [1] to biofeedback measurements [6,7,8]. Recent approaches combine different kinds of information channels to increase the prediction of

the emotional and cognitive learner states [9]. In the field of biofeedback measurements, few researches were done and many tracks remain unexplored.

Our previous works focused on using the Electroencephalogram (EEG) and collecting brainwaves during learning tasks [6,7,8]. Results show that the student's affect (Anger, Boredom, Confusion, Contempt, Curious, Disgust, Eureka, and Frustration) can be accurately detected (82%) from brainwaves [7]. We have also conducted an experimentation in which we explored the link between brainwaves and emotional assessment on the SAM scale (pleasure, arousal and domination). Results were promising, respectively with 73.55%, 74.86% and 75.16% accuracy for pleasure, arousal and dominance [8]. Those results support the claim that all rating classes for the three emotional dimensions (pleasure, arousal and domination) can be automatically predicted with a good accuracy through the nearest neighbour algorithm. These results suggest that inducing some brainwave states could help learners increase their ability to concentrate and decrease their stress levels.

This time we are interested in the test period. We want to track the electrical brain activity of a learner when he is answering questions. A learner can guess the right answer or not and when he answers he indicates if he is sure or not. The question of this paper would be then "Can we predict the learner's answer from his brainwaves?"

We believe that the cognitive state has an impact on brainwaves which inform about the learner's answer. In order to investigate this hypothesis, this paper has reached three objectives. The first one was to conduct an experiment to record the electrical brain activity of 23 participants when they were answering 35 questions. The second objective was to use machine learning technique to predict the learners' answer from his brainwaves. The third objective was to complete our previous work and implement an agent to be added to the architecture of a multi-agent system that measures brainwaves and predicts efficient learner's metrics.

1.1 Measuring the Brainwaves

Brain activity is characterized by the production of electrical signals reflected in brain waves. These are of very low voltage and are measured in Hertz or cycles per second. Brainwaves are rapid fluctuations of voltage between parts of the brain that are detectable with an EEG. Bioinformation allows us to reorganize the brain's activities through mental training.

The brainwaves that we measured were categorized into 6 different frequency bands, or types. According to their frequency, the waves are given the following names : delta, theta, alpha, β_1 , β_2 and β_3 waves. Each of these wave type correlates with a particular mental state [14]. Table 1 lists the different frequency bands and their associated mental states. The performance of our mind depends on the predominant type of wave at any given moment:

Research has shown that although one brainwave state may predominate at any given time, depending on the activity level of the individual, the remaining five brain states are present in the mix of brainwaves at all times. In other words, while somebody is in an attentive state and exhibiting a β_2 brainwave pattern, there also exists in that person's brain a component of β_3 , β_2 , alpha, theta and delta, even though these may be present only at the trace level.

Table 1. Brainwaves and Mental States

Wave	Frequency	Mental State
Delta	0-4 Hz	Deep sleep. Hypnosis. Increasing immune functions. Physical and mental restructuring.
Theta	4-8 Hz	Deep relaxation. State of meditation. Increase in creativity. Mental and muscular relaxation. Positive thought. Improved memory. Assimilation and capacity for study. Improved performance in sport.
Alpha	8-12 Hz	Relaxed focus. Improved attention.
Beta ₁	12-15 Hz	Vigilance. Logical reasoning. Conscious attention.
Beta ₂	15-20 Hz	Fully awakened state. Vigilance. Tension-anxiety-stress.
Beta ₃	> 20 Hz	Confusion. Irritability. Psychosomatic problems.

2 Study Methodology

Initially, we selected 24 undergraduates from the Computer Science Department at University of Montréal. 3 of them were discarded because their low French language level of comprehension. One day before the experiment, participants were asked to read one time and carefully a set of 7 articles. They were selected from old French newspapers. On the day of the experiment, we recorded the brainwaves of each participant when he was answering the 35 questions related to the 7 texts he read before (Figure 1).

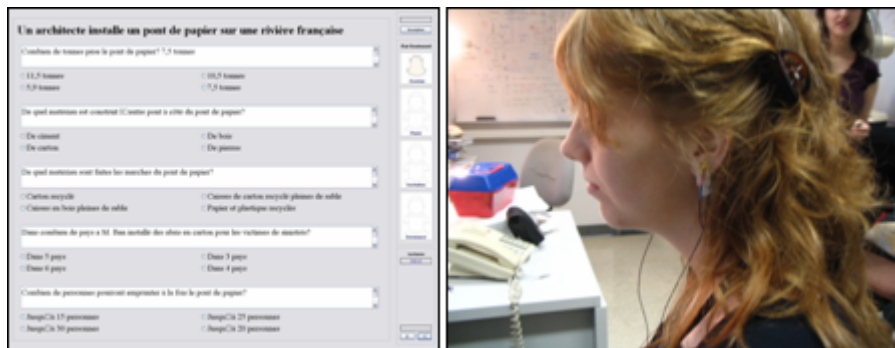


Fig. 1. The Test Interface on the left and the participant wearing Pendant EEG on the right

The EEG used is *Pendant EEG* [12]. Pendant EEG sends electrical signals to the computer via infrared connection. The electrical signal recorded by the EEG is sampled, digitized and filtered to divide it into different frequency bands. Light and easy to carry, Pendant EEG is not cumbersome and can easily be forgotten within a few minutes. The learner wearing Pendant EEG is completely free of his movements: no cable connects him/her to the computer. When asked a question, a participant indicates if he knew the answer or if answers randomly. In both cases, the answer could be right or false. Table 2 shows the whole possibilities. The test duration's varies from 15 to 20 minutes for each participant.

Table 2. Learner's types of answers to the questions

Code	Answer	Meaning
RG	Right: Guessed	The learner knew the answer and he guessed right
RR	Right: Random	The learner did not know the answer but he guessed right
FG	False: Guessed	The learner thinks he knew the answer but he does not
FR	False: Random	The learner did not know the answer and he guessed false

Over 2 weeks and for a total duration of 30 hours, we collected 45827 recordings in the database. We had 17157 recordings of RG answers, 10803 of FR answers, 5608 of RR answers and 12259 FR answers. Right answers represent 49.68% of the sample. Among of the right answers, 24.63% were a RR answers.

4 Machine Learning: Training and Results

For classification we used WEKA, a collection of machine learning algorithms recommended for data mining problems implemented in Java and open sourced under the GPL [16]. The problem of determining the learner's answer types from the brainwaves amplitudes can be represented as the following mapping function.

$$f[Amplitude(\delta, \theta, \alpha, \beta_1, \beta_2, \beta_3)] \rightarrow answer \quad (1)$$

Many classification algorithms were tested. The best results were given respectively by the algorithms: Classification via Regression, Decision Tree, Bagging, Random Forest and k-Nearest Neighbour (k=1). Table 3 shows the overall classification results using k-fold cross-validation (k = 10). In k-fold cross-validation the data set (N) is divided into k subsets of approximately equal size (N/k). The classifier is trained on (k-1) of the subsets and evaluated on the remaining subset. Accuracy statistics are measured. The process is repeated k times. The overall accuracy is the average of the k training iterations.

The various classification algorithms were successful in detecting the learner answers' types from his brainwaves. Classification accuracy varies from 90% to 98%. Furthermore, Kappa statistic scores is excellent, they vary from 0.87 to 0.98. Kappa statistic measures the proportion of agreement between two rates with correction for chance. Kappa scores ranging from 0.4 – 0.6 are considered to be fair, 0.6 – 0.75 are good, and scores greater than 0.75 are excellent.

Table 3. Best Accuracies

Algorithm	Accuracy	Kappa Statistic	Mean Absolute Error
Classification Via Regression	90.62%	0.87	0.16
Decision Tree (J48)	91.60%	0.88	0.05
Bagging	96.56%	0.95	0.10
Random Forest	98.36%	0.98	0.04
K-Nearest Neighbor (K=1)	98.57%	0.98	0.01

Table 4. Detailed accuracy by Class

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
0.987	0.008	0.987	0.987	0.987	RG
0.985	0.005	0.984	0.985	0.985	FG
0.981	0.003	0.981	0.981	0.981	RR
0.986	0.005	0.987	0.986	0.986	FR

For the k-Nearest Neighbor (k=1) algorithm, table 4 shows the details of classification accuracy among the 4 classes (the 4 types of the learner's answers).

5 Conclusion and Perspective

This study used machine learning techniques to test the hypothesis: “We can predict the guessed and the random learner’s answers from his brainwaves”. 21 participants were recruited and 45827 instances were recorded into the database. We used Pendant EEG to measure the brainwaves while the participants were asked to answer some questions related to the texts they read the day before. The participant wearing Pendant EEG is completely free of his movements: no cable connects them to the machine. Pendant EEG sends the electrical signals to the machine via an infrared connection. With this infrastructure, we reduced the possible side effect of the material. We acknowledge that the use of EEG has some potential limitations. In fact, any movement can cause noise that is detected by the electrodes and interpreted as brain activity by Pendant EEG. However, we gave very strict instructions to our participants. They were asked to remain silent, immobile and calm. We believe that the instructions given to our participants, their number (21) and the database size (45827 records) were able to considerably reduce this eventual noise. Results are encouraging. In fact, the K-means analyses resulted in accurate predictions 98.57% and the Yuden’s J-Index is 98.46%. These results show that we could incorporate an agent into our previous multi-agent system that send this information to an ITS to improve the pedagogical strategy and influence the learner brainwaves for a better results. An ITS should select an adequate pedagogical strategy that adapt to certain learner’s mental states correlated to the brainwaves frequency bands in addition to cognitive and emotional states.

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References

1. Ahn, H.I., Teeters, A., Wang, A., Breazeal, C., Picard, R.W.: Stoop to Conquer: Posture and affect interact to influence computer users’ persistence. In: Paiva, A.C.R., Prada, R., Picard, R.W. (eds.) ACII 2007. LNCS, vol. 4738, pp. 582–593. Springer, Heidelberg (2007)
2. Anderson, J.R.: Tailoring Assessment to Study Student Learning Styles. In: American Association for Higher Education, vol. (53), p. 7 (2001)

3. Boyer, K.E., Phillips, R., Wallis, M., Vouk, M., Lester, J.: Balancing Cognitive and Motivational Scaffolding in Tutorial Dialogue. In: Woolf, B.P., Aïmeur, E., Nkambou, R., Lajoie, S. (eds.) ITS 2008. LNCS, vol. 5091, pp. 239–249. Springer, Heidelberg (2008)
4. D’Mello, S., Jackson, T., Craig, S., Morgan, B., Chipman, P., White, H., Person, N., Kort, B., el Kaliouby, R., Picard, R.W., Graesser, A.: AutoTutor Detects and Responds to Learners Affective and Cognitive States. In: Workshop on Emotional and Cognitive Issues at the International Conference of Intelligent Tutoring Systems, Montreal, Canada, June 23-27 (2008)
5. Grandbastien, M., Labat, J.M., et al.: Environnements informatiques pour l’apprentissage humain. Éditions, Lavoisier, Paris, France (2006)
6. Heraz, A., Daouda, T., Frasson, C.: Decision Tree for Tracking Learner’s Emotional State predicted from his electrical brain activity. In: Woolf, B.P., Aïmeur, E., Nkambou, R., Lajoie, S. (eds.) ITS 2008. LNCS, vol. 5091, pp. 822–824. Springer, Heidelberg (2008)
7. Heraz, A., Razaki, R., Frasson, C.: Using machine learning to predict learner emotional state from brainwaves. In: ICALT, Niigata, Japan (2007)
8. Heraz, A., Frasson, C.: Predicting the Three Major Dimensions of the Learner’s Emotions from Brainwaves. *International Journal of Computer Science* (2007)
9. Kapoor, A., Ahn, H.I., Picard, R.W.: Mixture of Gaussian Processes for Combining Multiple Modalities. In: Oza, N.C., Polikar, R., Kittler, J., Roli, F. (eds.) MCS 2005. LNCS, vol. 3541, pp. 86–96. Springer, Heidelberg (2005)
10. Kort, B., Reilly, R., Picard, R.W.: An Affective Model of Interplay Between Emotions and Learning: Reengineering Educational Pedagogy-Building a Learning Companion. In: Proceedings of International Conference on Advanced Learning Technologies (ICALT 2001), Madison, WI (August 2001)
11. Lang, P.J., Bradley, M.M., Cuthbert, B.N., et al.: International affective picture system (IAPS): Affective ratings of pictures and instruction manual. Technical Report A-6. University of Florida, Gainesville, FL (2005)
12. McMillan Bruce (2006), <http://www.pocket-neurobics.com>
13. Nkambou, R.V.: Facial expression analysis for emotion recognition in ITS. In: ITS 2004 workshop on Emotional Intelligence proceedings (2004)
14. Norris, S.L., Currier, M.: Performance enhancement training through neurofeedback. In: Evans, J.R., Abarbanel, A. (eds.) *Introduction to Quantitative EEG and Neurofeedback*. Academic Press, London (1999)
15. Wenger, E.: *Artificial Intelligence and Tutoring Systems*. Morgan Kaufmann, Los Altos (1987)
16. Witten Ian, H., Frank, E.: *Data Mining: Practical machine learning tools and techniques*, 2nd edn. Morgan Kaufmann, San Francisco (2005)