

Predicting Stress Level Variation from Learner Characteristics and Brainwaves

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Abstract. It is very common that students fail their exam because of an excessive stress. However, an attitude with no stress at all can cause the same thing as stress which in turn can be beneficial in some learning cases. Studying the stress level variation can then be very useful in a learning environment. In this paper, the aim is predicting the stress level variation of the learner in relation to his electrical brain activity within an experiment over two days. To attain that goal, three personal and non-personal characteristics were used: the gender, the usual mode of study and the dominant activity between the first and second day. 21 participants were recruited for our experiment. Results were very encouraging: an accuracy of 71% was obtained by using the ID3 machine learning algorithm.

Keywords. Intelligent Tutoring Systems, Learning, Brainwaves, Stress Level Variation

Introduction

“Brain cells create ideas. Stress kills brain cells. Stress is not a good idea” - Richard Saunders

Recognizing and addressing the stress level variation of learners is one of the important roles of an expert teacher. Based upon that observation, a teacher can react with a specific behaviour that will have a positive impact on learning. For example, a teacher can distinguish whether a learner is making mistakes and does not need intervention (because he is willing to fail until he or she succeeds without aid) or whether the learner is growing increasingly stressed because he is making mistakes and thus likely will get frustrated. This ability is important in order to support the learning process and we want to add it to the capabilities of an Intelligent Tutoring System (ITS). To reach this goal, we measure the stress level variation by recording the electrical brain activity (brainwaves) of the learner at different periods. Brainwaves inform about the learner stress level. Our hypothesis is that gender, mode of study and the activity they did the most in 24 hours prior to the testing session (predominant activity), play a key to the stress level variation. Thus, we examine if these channels of information can provide useful indication for identifying the stress level variation, so that the ITS might ultimately formulate a more appropriate response, providing progressive guidance to the learner in order to regulate his stress level and improve knowledge acquisition.

In the field of Human-Computer Interactions (HCI), many researchers focus on detecting stress according to different contexts. SmartCar [3] is a set of smart physiological sensors embedded in an automobile to afford a novel opportunity to capture naturally occurring episodes of driver stress. Electrocardiogram, electromyogram, respiration and skin conductance sensors were used to measure autonomic nervous system activation. The signals were digitized in real time and stored on the SmartCar's pentium class computer. Using multiple sensory inputs improved performance significantly over the best single feature performance (62.2%). In another initiative, a mobile system that interrupts the wearer was implemented to support self-monitoring of stress. Many assessment techniques were used, including relative subjective count, which compares the difference in perceived number of interruptions to actual number of interruptions [4].

Unfortunately, few papers addressed the detection of stress variation during an ITS-managed learning session where learner interactions are omnipresent. In addition, most of the currently available assessment techniques are notoriously unreliable (Self-reported feelings) or difficult to achieve (getting outside observers to rate the learner behaviour) [2].

Because learners often try to appear calm when they are not [11], it is very hard to know if a learner is stressed or not. In this paper, we address the problem of detecting the stress level variation by measuring the learner brainwaves and exploring the influence of gender, mode of study and dominant activity of the learner during the 24 hours prior to the learning session. We used machine learning techniques to predict the stress level variation.

1. Collecting data

We ran an experiment over a two-days period. The main idea is to teach a specific material on day one and ask each learner to come back exactly 24 hours later to get tested on what they were taught. 24 participants were recruited from the Computer Science Department (University of Montreal). We used the electroencephalogram Pendant EEG [8] to measure the learner brainwaves for both days. Pendant EEG sends electrical signals to the computer via an infrared connection. Light and easy to carry, it is not cumbersome and can easily be forgotten within a few minutes. The learner wearing Pendant EEG is completely free of his movements as shown in Figure 1.

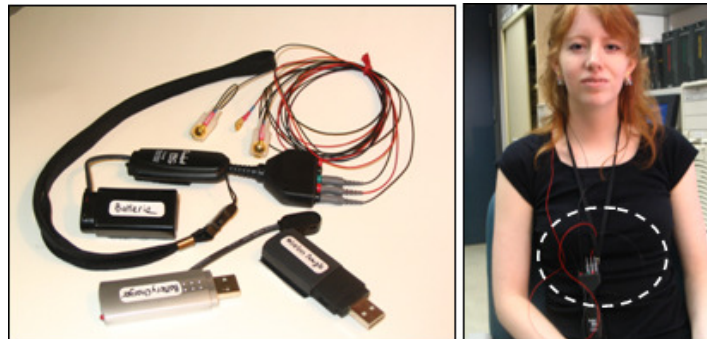


Figure 1. Pendant EEG on the left and the Learner wearing it on the right

Between days one and two, participants were asked to fill up a form in describing hourly the type of the main activities they did.

1.1. First and second day

As briefly mentioned earlier, participants read texts during the first day and answered questions during the second day. Meanwhile, Pendant EEG records and sends electrical signals to the computer via infrared connection. Table 1 shows the electrical signal recorded by the EEG, sampled, digitized and filtered into 6 frequency bands. [9]

Table 1. Brainwaves Categories

Wave Type	Frequency	Mental State
Delta (δ)	0-4 Hz	Deep sleep
Theta (θ)	4-8 Hz	Creativity, dream sleep, drifting thoughts
Alpha (α)	8-12 Hz	Relaxation, calmness, abstract thinking
Beta1 (β_1)	12-15Hz	Relaxed focus
Beta2 (β_2)	15-20Hz	High alertness
Beta3 (β_3)	+20 Hz	Stress

When Beta 3 is dominant (which means that it has the highest amplitude recorded), the learner is stressed.

1.2. The 24 Hours preceding the test

Figure 2 shows an extract of the form that was given to the participants and from which we can distinguish 5 types of activities that have to check hourly. They choose the predominant one to indicate only one activity type per hour.

1. Sleep: state of dormancy, inactivity
2. Meditation: state of contemplation or spiritual introspection
3. Relaxation: abatement or relief from bodily or mental work, effort, application, etc
4. Concentration: exclusive attention to one object; close mental application
5. Agitation: psychological and physical restlessness, manifested by pacing, hand-wringing, or other activity.

Twenty-four hours activity form					
Learner_Name:			Learner_ID:		
Hour	Sleep	Meditation	Relaxation	Concentration	Agitation
H1	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
H2	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
H3	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
H4	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
...
H24	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure 2. Extract from the form that describes the activities between the two days

2. Training data

Our objective is to identify the main factors involved in the variation (positive or negative) of a learner's stress level following learning activity of day one. Can we establish that personal as well as non-personal characteristics of learners allow us to predict whether the learner's stress level would tend to increase or decrease between the two days ?

We created a database of vectors values representing dominant brainwave fluctuations for each learner. Each vector contains six values associated with the following brainwave categories: alpha, beta1, beta2, beta3, delta and theta. These values are sorted according to the dominant category in an ascending order. Thus, the first element of the vector is the value of the most dominant brainwave category. An example of such vector might be: $v = \{\text{beta2}, \text{beta3}, \text{alpha}, \text{theta}, \text{delta}, \text{beta1}\}$. Such a vector informs us that the strongest dominant category (both in term of amplitude and frequency) is beta2 as opposed to the least dominant beta1. It is important to state that every change in the dominance of emitted brainwave categories will trigger a recording of a new vector for the learner in question. For example, if at a moment, the vector of a person is $\{\text{beta2}, \text{beta3}, \text{alpha}, \text{theta}, \text{delta}, \text{beta1}\}$ and the first two dominances have switched (for instance beta3 became the most dominant category), then we will have the following new record for this individual: $\{\text{beta3}, \text{beta2}, \text{alpha}, \text{theta}, \text{delta}, \text{beta1}\}$. Furthermore, we have recorded for each learner, a specific number of vectors. This number obviously differs from the first to the second day and from a learner to another. We used this number as a characteristic of the learner's brain behavior.

For each learner, we considered the proportion of the first dominance of each brainwave category and we focused on the percentages of the beta3 category because it is indicative of stress. That is, we weighted the number of beta3 first dominance vectors by the total number of vectors emitted by the learner during the experiment. This proportion indicates the extent a witch the learner has been stressed.

3. Results

A total of 23 participants took part in experiment from which two were eliminated because of their bad understanding of the French language. Table 2 shows a sample from the 21 learners' percentages of beta3 waves, for the two days. The data in this table represent the proportion of beta3 dominance associated with stress present in the dominance vector that we computed from the EEG recordings.

Table 2. Proportion of beta3 presence

learner_id	1st day	2nd day
1	42.62%	15.47%
2	27.24%	18.88%
3	28.73%	25.43%
4	26.53%	24.82%
...
18	23.97%	57.95%
19	16.10%	30.97%
20	17.46%	41.54%
21	10.23%	28.54%

During these experiments, it was rather expected that the stress level would increase during the second day given that the first day's activity was a reading exercise and the second day's activity was an exam. Surprisingly, it was found that the level of beta3 (stress) could decrease for some learners as depicted by Figure 3.

Moreover, this variation could be substantial in both directions. For example, Table 2 shows the first learner who was stressed most of the time during the first day, (Id=1, 42.62% of beta3 dominance) seemed to be much more relaxed on the second day (only 15.47% of beta3 dominance). In the same way, for learner number 20 who was quite relaxed on the first day (17.46% of beta3 dominance), has shown a large increase of his stress level (quite the double) on the second day (41.54% of beta3 dominance).

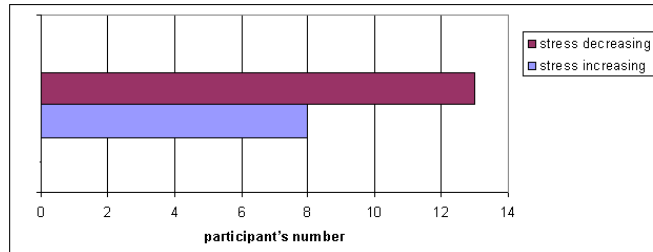


Figure 3. Stress variation between the first and the second day

In order to explain this phenomenon, we studied three variables of learner characteristics variables namely the gender, the mode of study and the dominant activity during the twenty-four hours separating the two days. The description of the participant's variables is given in Table 3 and Figure 4.

Table 3. Participant's description

Mode of study	Female	Male	Total
Silence	6	8	14
Noise	1	3	4
Music	2	1	3
Total	9	12	21

To see whether a relationship exists between the learner's characteristics and their dominant brainwaves, we predicted the direction of the variation in the level of stress on the basis of the gender, mode of study and the twenty-four hours dominant activity. We then considered two classes for learners: those whose stress level increased from the first to the second day, and those whose stress level decreased.

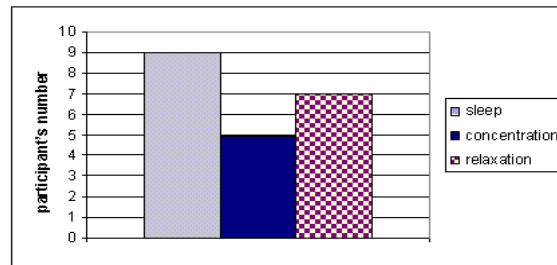


Figure 4. Twenty-four hours dominant activities

For the prediction, we used a machine learning technique namely the ID3 algorithm [1] with a ten fold cross-validation. This algorithm produced a decision tree by computing the information gained for each attribute and selecting the greatest one. This tree is presented in Figure 5. Each level of the tree, between the root and leaves, is one of the three attributes considered for each learner. The root of the tree represents the learner as a starting point to predict his stress variation direction class represented by the leaves of the tree. The first level is one of the three possible modes of study: silence, music or noise. The second level represents the twenty-four hours dominant activity including: sleep, concentration or relaxation and the third level is the learner gender.

According to this tree, a learner who is used to study in a silent environment, who spends most of the time between the two days concentrated and who is a female, will have his stress level decrease in the second day. On the other side, students whose usual mode of study is music tend to be less stressed when answering a test.

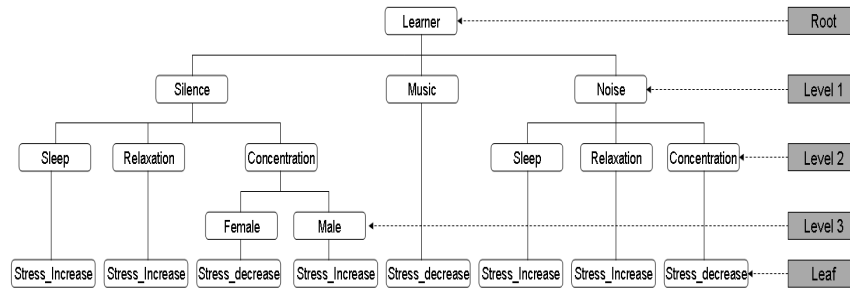


Figure 5. Decision tree associated to the stress variation direction prediction

Table 4 presents a summary of overall results and Table 5 shows the details of accuracy. These results show that we could predict with more than 70% the stress level variation direction class if we know the learner’s characteristics (mode of study, twenty-four hours dominant activities and gender).

Table 4. Summary of the evaluation on test split

Correctly Classified Instances	Incorrectly Classified Instances	Kappa statistic	Unclassified Instances
71.4286 %	23.8095 %	0.4186	4.7619 %

We obtained a percentage of correct classification of 71.4% with an acceptable Kappa. On the other hand, precisions are quite accurate with 0.706 for the stress_increase class and 1 for the stress_decrease class.

Table 5. Detailed accuracy by class

Class	TP Rate	FP Rate	Precision	Recall	F-Measure
stress_increase	1	0.625	0.706	1	0.828
stress_decrease	0.375	0	1	0.375	0.545

From these results, we are able to claim that a relationship between the learner’s features (gender, mode of study and activity of twenty-four hours) and the increase or decrease of the level of stress between the two days of learning seems plausible. Furthermore, we are able to predict that variation with an acceptable accuracy.

4. Communication with an ITS

In our previous work, we implemented 4 agents that receive the brainwaves signals and predict from it different learner's characteristics like emotion (Emotional Agent) [5], the emotional dimensions: pleasure, arousal and dominance (PAD-Mental Agent) [6] and positive and negative Learning and Emotion (QelMental Agent) [7]. This paper presented other interesting results related to detect the stress variation. Thus, we are currently implementing the Stress Prediction Agent (SP Agent). By communicating with an ITS via the JADE (Java Agent Development Framework) platform [10] in the FIPA-ACL language. SP Agent sends information to the ITS to inform about the stress level variation of the learner. The ITS will then respond with appropriate strategies to regulate the learner's stress. Figure 6 shows the overall architecture.

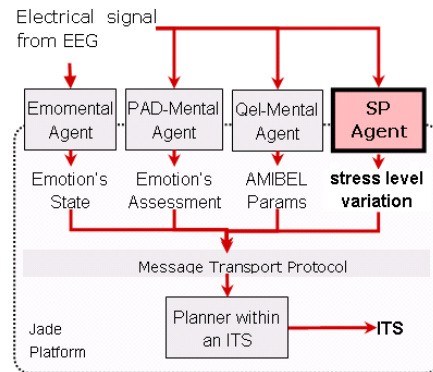


Figure 6. Communication between the Stress Prediction Agent and an ITS

The current results and decision tree of our SP Agent will enable us to complete our multi-agent platform.

5. Conclusion

We have established in this paper a relationship between a learner's personal and non-personal characteristics and his dominant beta3 brainwave category enabling us to predict, seven times out of ten, his stress level variation. In the conducted study, we recorded the learner's brainwave activity in two separate days. Brainwave activity was filtered and computed as a dominant wave vector and saved in our system. Moreover, we collected hourly inputted data from the participant indicating the activities they attended to during the 24 hour period preceding the test. Mixed with the gender and mode of study, our statistical analysis enabled us to predict, with a very encouraging accuracy of 70%, the probability of either stress increase or decrease. Indeed, the resulting decision tree utilizes the three mentioned characteristics to predict the learner's expected stress levels.

Two main contributions stand out from this paper. First, we established a link between a set of characteristics and stress level variation which can be very helpful to consider in any given learning activity. Second, our SPA, once implemented, can seamlessly integrate with our already existing multi-agent platform, thus augmenting its efficiency and intervention quality. We intend in the near future to study a much

broader set of features with regards to stress levels in the hope of maximizing the accuracy rate of the agent. Furthermore, we also intend to integrate this agent in our Multi-Agent platform called Nora and validate its efficiency once integrated.

Acknowledgments

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