Predicting Stress Level Variation from Learner Characteristics and Brainwaves

Alicia HERAZ, Imène JRAIDI, Maher CHAOUACHI and Claude FRASSON
HERON Lab; Computer Science Department; University of Montréal,
CP 6128 succ. Centre Ville Montréal, QC, H3T-1J4, Canada
{herazali, jraidiim, chaouacm, frasson}@iro.umontreal.ca

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 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: gender, usual mode of study and 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

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. 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 [6], 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 a machine learning technique to predict the stress level variation.
1. Experiment

We ran an experiment over a two-days period. 21 participants were recruited from the Computer Science Department. Participants read texts during the first day and answered questions during the second day. Meanwhile, the electroencephalogram Pendant EEG [5] records and sends electrical signals to the computer via infrared connection. Table 1 shows the recorded brainwaves and their associated mental states.

<table>
<thead>
<tr>
<th>Wave Type</th>
<th>Frequency</th>
<th>Mental State</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta (δ)</td>
<td>0-4 Hz</td>
<td>Deep sleep</td>
</tr>
<tr>
<td>Theta (θ)</td>
<td>4-8 Hz</td>
<td>Creativity, dream sleep, drifting thoughts</td>
</tr>
<tr>
<td>Alpha (α)</td>
<td>8-12 Hz</td>
<td>Relaxation, calmness, abstract thinking</td>
</tr>
<tr>
<td>Beta1 (β1)</td>
<td>12-15Hz</td>
<td>Relaxed focus</td>
</tr>
<tr>
<td>Beta2 (β2)</td>
<td>15-20Hz</td>
<td>High alertness</td>
</tr>
<tr>
<td>Beta3 (β3)</td>
<td>+20 Hz</td>
<td>Stress</td>
</tr>
</tbody>
</table>

Between days one and two, participants were asked to fill up a form describing hourly the type of the main activities they did. There were 5 types of activities to check hourly: sleep, mediation, relaxation, concentration and agitation.

2. Results

Our objective is to identify the main factors involved in the variation of the stress level. We then recorded vector values representing dominant brainwave fluctuations for each learner. Each vector contains six values associated with brainwave categories. These values are sorted according to the dominant category in an ascending order and every change in the dominance of emitted brainwave categories will trigger a recording of a new vector. That way, 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. For each learner, we considered the proportion of the first dominance of each brainwave category among the total number of vectors and we focused on the percentages of beta3 category that indicates the stress level [5]. Table 2 shows a sample from the 21 learners’ percentages of beta3 waves, for the two days.

<table>
<thead>
<tr>
<th>learner id</th>
<th>1st day</th>
<th>2nd day</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>42.62%</td>
<td>27.24%</td>
</tr>
<tr>
<td></td>
<td>15.47%</td>
<td>18.88%</td>
</tr>
</tbody>
</table>

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. In order to explain this phenomenon, we studied three characteristics of the learners: gender, twenty-four hours dominant activity and the usual mode of study (silence, noise or music). These variables were used to predict the direction of the variation in the level of stress. 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.

We used a machine learning technique namely the ID3 algorithm [1] that produced a decision tree by computing the information gained for each attribute and selecting the
This tree is presented in Figure 1. 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.

**Figure 1.** Decision tree associated to the stress variation direction prediction

This algorithm predicted the stress level variation direction with 71.4 percent of correct classification. On the other hand, precisions are quite accurate with 0.706 for the stress_increase class and 1 for the stress_decrease class.

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.

**Conclusion**

In this paper, we have established a relationship between a learner’s personal and non-personal characteristics and his dominant beta3 brainwave category. In the conducted study, we recorded the learner’s brainwave activity in two separate days. Moreover, we collected hourly inputted data from the participant indicating the activities they attended to during the 24 hours preceding the test. Mixed with the gender and mode of study, our statistical analysis enabled us to predict either stress increases or decreases with a very encouraging accuracy of 71%.

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**References**


