Using machine learning to predict learner emotional state from brainwaves

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Abstract

Intelligent Tutoring Systems (ITS) learner model has progressively evolved. Initially composed of a cognitive module it was extended with a psychological module and an emotional module. The learner model still remains non-exhaustive. Methods of data collection on the cognitive and emotional state of the learner often lack precision and objectivity. In this paper we introduce an emomental agent. It interacts with an ITS to communicate the emotional state of the learner based upon his mental state. The mental state is obtained from the learner's brainwaves. The agent learns to predict the learner's emotions by using machine learning techniques.

Introduction

The learner model is an important component of an ITS. It is via that model that the tutor adapts the training environment in order to answer the needs, objectives and interests of the learner [17]. The learner model has gradually evolved. At the beginning, it included the learner's knowledge, also called *cognitive profile* [23]. Later on, psychological characteristics related to learning, such as motivation, sensory preferences and learner's personality were introduced [11]. That extension is also called the *psychological profile*. The necessity to take into account more information appeared with recent studies on learners' *emotional states* [13] [4]. Most of current researches in user modeling explore the links between emotions and learning. A lot of these works focus on predicting learner's emotions during his interaction with an ITS [8].

Unfortunately, many of those systems look at the learner's external appearance. They use video camera, sensors, and classification algorithms to analyze facial expressions [13][20] or verbal tones [6]. However, for impassive, taciturn and/or handicapped learners, these methods lack performance and current learner models are therefore insufficient. Moreover, psychological approaches for detecting emotional states are often subjective and skewed [9]. To avoid such ambiguity we have oriented our work to detection of learner's brainwaves while he is involved in an educational activity. We make the hypothesis that there is a strong correlation between these signals and emotional states. This detection can strengthen previous approaches to finally build a more precise learner model. In fact, a multimodal approach is strongly required for increasing the prediction of the learner's emotional state [21].

In this paper, we intercept brainwaves with non-invasive brain-computer interfaces [1] that read brain signals using an electroencephalogram (EEG). EEG-based brain-computer interfaces use sensors placed on the head to detect brainwaves and transmit them to a computer for further processing and analysis [22]. We aim to associate the emotional state of a learner with his *mental state.* We call this new state: *learner's emomental state* and we propose to design an *emomental agent* for measuring and managing this state. In the present paper we will show how such an agent can be built by using machine learning techniques in order to associate each mental state to an emotional state. Section 1 of this paper defines the *emomental state*, section 2 describes the experimentation process, section 3 details the machine learning process and discusses the results, and finally section 4 presents the implementation of our agent.

1. The emomental state

We define an *emomental state* as the component which contains the two following information: the mental state and the emotional state. A mental state is a vector which includes the recorded amplitudes of each of the four brainwaves detailed in table 1 and the emotional state from the list shown in table 2. In fact, in the brain, four basic types of waves can be distinguished. Each of these waves can be a dominant wave in a period of time. When a brainwave is the dominant wave, it gives information about the learner state (Table 1). Each wave is identified by amplitude and an interval of frequencies.

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Table 1: brainwaves

Wave Type	Frequency	When wave is dominant
δ Delta	0-4 Hz	Deep sleep
θ Theta	4-8 Hz	Creativity, dream sleep drifting thoughts
α Alpha	8-12 Hz	Relaxation, calmness, abstract thinking
β Beta	+12Hz	Relaxed focus. High alertness, mental activity. Agitation, anxiety

We are not interested in all emotional states. Those which occur frequently during learning are anger, boredom, confusion, contempt, curious, disgust, eureka, and frustration [6]. Table 2 defines each one of these emotions.

Table 2: emotions occurring during learning

Emotion	Description
Anger	a strong feeling of displeasure and usually of antagonism
Boredom	the state of being weary and restless through lack of interest
Confusion	to fail to differentiate from an often similar or related other
Contempt	the act of despising; lack of respect or reverence for something
Curious	an active desire to learn or to know
Disgust	marked aversion aroused by something highly distasteful
Eureka	a feeling used to express triumph on a discovery
Frustration	making vain or ineffectual all efforts however vigorous ; A deep chronic sense or state of insecurity and dissatisfaction arising from unresolved problems or unfulfilled needs

Initially, we aim to test different standard classification techniques and attempt to detect the learner's emotional state from mental state. After that, we will implement the better algorithm in our *emomental agent*. This one will communicate to an ITS the learner's emotional state when he interacts in a learning session. Let EmS be the emomental state. It is defined as follows:

$$EmS = \left(w_\delta, w_\theta, w_\alpha, w_\beta, e\right)$$

Where $\left(w_\delta, w_\theta, w_\alpha, w_\beta\right) \in \mathrm{N}^4$ are the four main amplitudes of the brainwaves and e is the emotional state, $e \in EL = \{Anger, Boredom, ..., Frustration\}$.

2. Experimentation

In our experimentation we wish to train the emomental agent to predict learner's emotional state. We use *Pendant EEG* [17], a portable wireless EEG. Electrode placement was determined according to the *10-20 International System of Electrode Placement*. This system is based on the location of the cerebral cortical regions. In our case, three electrodes were sufficient [16], they are placed on PC_z, A_1 and A_2 [3]. Pendant EEG sends the 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: no cable connects him to the computer (Figure 1).

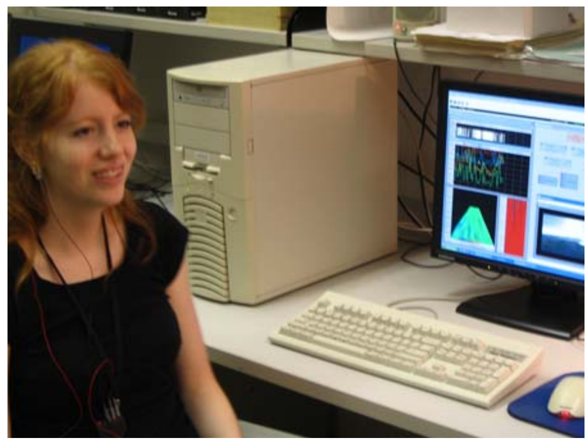

Figure 1: learner wearing Pendant EEG

The experiment includes 17 participants. They were selected from the Computer Science Department of Université de Montréal. In order to induce emotional states, we use IAPS (*International Emotional Picture System*) [14], a bank of 700 pictures. A participant is connected to Pendant EEG. He is invited to watch a random sequence of pictures from our database and to indicate his emotional state at any time, whenever it changes. Participants select one of the eight emotional states indicated in table 2. In case of need, he also can choose *neutral* or *other*. The duration of the experimentation for each participant varies between 15 and 20 minutes. Before watching pictures, the participant has to indicate his current emotional state. During the experimentation, he is free to stop when he wishes. Our purpose is to record the emomental state each time when the emotional state or the mental state values change. Throughout more than 300 minutes of experimentation's total duration, we recorded 32317 emomental states.

3. Machine learning process

Determining emotions from brainwaves can be cast as a multi-class classification problem. The mapping function to find is:

$$f : EmS = \left(w_\delta, w_\theta, w_\alpha, w_\beta\right) \rightarrow e$$

3.1. Data treatment

The two additional emotional states *neutral* and *other* are not among the original list of emotional states (table 2), thus, they were discarded from the analysis. This resulted in a further reduction in the database from 32317 to 19663 records, with 1746 instances of anger, 1294 of boredom, 1500 of confusion, 754 of contempt, 4217 of curious, 3937 of disgust, 5016 of eureka and 1208 of frustration. Amplitudes were normalized as follows:

$$w_i = \frac{w_i - \left(\frac{1}{n}\sum_{k=1}^{n} w_{ik}\right)}{\sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(w_{ik} - \left(\frac{1}{n}\sum_{k=1}^{n} w_{ik}\right)\right)^2}}$$

Where $i \in (\delta, \theta, \alpha, \beta)$ and $n = 19663 \times 4$ is the size of our database after cleaning multiplied by the four types of brainwaves.

For classification we used Weka, a collection of machine learning algorithms intended for data mining. The algorithms can be either applied directly to a dataset, or called from a Java program. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes [24].

3.2. Classification Results and discussion

Our database contains noise due to the limitations of the material used and the learners' response time. We took account of that in our choice of training algorithms. Among those that have the advantage of being robust to noisy training data and effective when that data is large, IBK gave us the best results. IBK is an implementation of k-nearest neighbors [7]. Given a query point it finds the k closest to the query point. In the experimentation we have used 70% of the dataset for training and 30% for testing. The use of the k-nearest neighbors algorithm requires determination of parameter K. The best results obtained were for k=1. The best percentage of correctly classified instances is 82.27% (Figure 2).

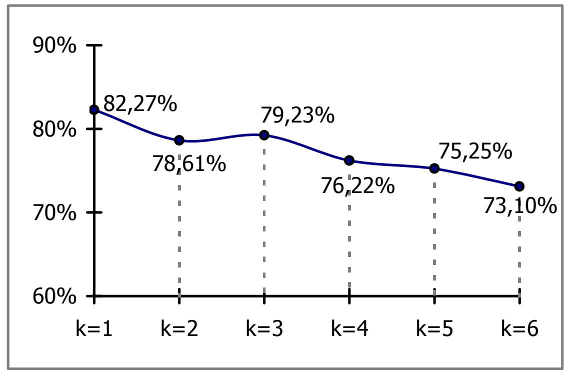

Figure 2: results among k values

Table 3 shows details on the accuracy by emotion.

Table 3: accuracy by emotion

Emotion	Precision	Recall	F-Measure
Anger	0.814	0.822	0.818
Boredom	0.8	0.796	0.798
Confusion	0.792	0.809	0.8
Contempt	0.798	0.787	0.792
Curious	0.814	0.817	0.816
Disgust	0.829	0.836	0.833
Eureka	0.84	0.831	0.835
Frustration	0.825	0.807	0.816

Classification precision varies between 79.2% and 84%. Recall varies between 78.7% and 82.2%. The performance of the classifier, given by F-Measure (Table 3) is computed as follows:

$$FMesure = \frac{2 \times \mathrm{Re}call \times \mathrm{Pr}ecision}{\mathrm{Re}call + \mathrm{Pr}ecision}$$

The performance of our classifier varies between 79.2% and 83.5%. The Kappa statistic measures the proportion of agreement between two raters 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 [15]. Our statistical value of kappa is 0.78. This shows a good agreement between real and predicted emotional states.

To give more weight to emotional states with minority instances, we decided to use Youden's J-index [25] defined as:

$$JIndex = Card(EL)^{-1} \sum_{e \in EL} \Pr ecision_e$$

With $Card(EL) = 8$ is the cardinality of emotional states list. The value of $JIndex = 81.2\%$ is close to our classification prediction (81.2% ≅ 82.27%). This means that the prediction is almost the same for all different emotional states. This can be seen on table 4. The greatest values are found in the diagonal of the matrix, which means that the majority of emotional states associated with mental states are correctly predicted.

Table 4: confusion matrix

Classified as	A	B	C	D	E	F	G	H
A:Anger	412	7	7	1	25	11	23	3
B:Boredom	8	318	5	0	18	12	19	7
C:Confusion	9	5	374	10	15	16	28	4
D:Contempt	8	0	5	166	11	12	9	0
E:Curious	13	25	23	10	1060	64	67	24
F:Disgust	18	12	18	6	52	976	72	13
G:Eureka	31	25	31	14	104	65	1262	9
H:Frustration	9	12	8	1	11	17	14	285

Our results on the link between emotional states and mental states are encouraging. According to this hypothesis, we implemented the *emomental agent*.

4. Architecture of the emomental agent

The emomental agent predicts the emotional state from the mental state. It includes the four following main modules (figure 3): *electrical signal acquisition module*, *electrical signal treatment module*, *emotional state induction module* and *emotional state classification module*. The emomental agent will communicate with an ITS to send him the emotional state predicted from the learner's mental state.

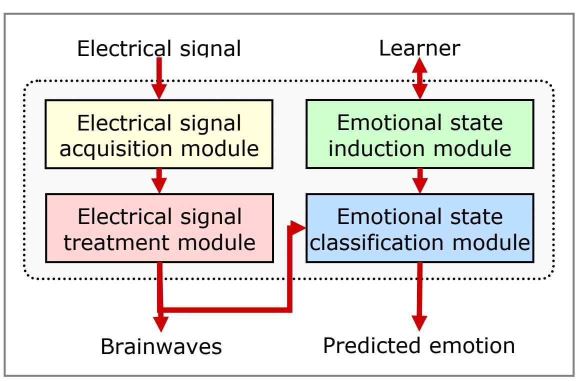

Figure 3: the emomental agent Architecture

The *electrical signal acquisition module* intercepts the learner's brainwaves in form of electrical signal. This one can be recorded in files specific to the standard EDF format [12]. In our case, data is treated in real time. The electrical signal requires additional processing to provide useful information. In order to analyze the amount of brain activity in a particular frequency band, such as alpha (8-12 Hz), the activity in this frequency range must be separated out. That is the function of the *electrical signal treatment module*. The *emotion induction module* uses stimuli to induce a positive emotional state when the current emotional state is negative [13]. The *emotional classification module* predict the learner's emotional state from his brainwaves and send it to an ITS.

The emomental agent communicates with the planner located in the tutoring module of an ITS. It sends to the latter the predicted emotional state. Communication occurs under the JADE platform (Java Agent Development Framework) [2]. JADE is a multi-agent platform developed in Java by CSELT (research Group of Gruppo Telecom, Italy). This is done according to the communication language FIPA-ACL. As an example, the exchange below is one of the shorter tutorial dialogues between the emomental agent and the planer of an ITS.

```
INFORM {
: SENDER= (Emomental agent);
: RECEIVER= (Planner);
: CONTENT= (confusion);
}
```

The emomental agent can be integrated in a multi-agent STI. It can be useful in the case of disabled, taciturn or impassive learners.

5. Conclusion and future work

This paper argues for the use of brainwaves to predict emotional states in an ITS in the case of disabled, taciturn or impassive learners. Our experimentation allowed us to constitute a large dataset. To classify different recorded mental states, nearest neighbor was the algorithm that yielded the best classification prediction: 82.27%. It appears that there are significant relationships between brainwaves and emotional states experienced during learning. To verify this hypothesis, we implemented an agent called the emomental agent. It communicates with an ITS under JADE platform. If the

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grounding criterion hypothesis holds in future replication, then it would give indications on how to help certain learners control their emotional states by controlling their brainwaves. For example, by using neurofeedback, a technique which feeds to the learners their brainwaves on a brain-computer interfaces. If brainwaves method described above prove to be effective in identifying the learner's emotional state, we can direct our focus developing new pedagogical strategies in the future.

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