

Detecting the Affective Model of Interplay between Emotions and Learning by Measuring Learner's Brainwaves

Alicia Heraz and Claude Frasson

HERON Lab, University of Montréal,
CP 6128 succ. Centre Ville
Montréal, QC, H3T 1J4
{herazali,frasson} @iro.umontreal.ca

Abstract. The Affective model of Interplay between Emotions and Learning (AMIBEL) is a model proposed by Kort et al. (2001) to illustrate the link between emotions and learning. According to this model, both positive and negative learning can be enhanced by either positive or negative emotions. This paper investigates how the use of machine learning techniques can significantly predict the AMIBEL from brainwaves. This study has adopted an experimentation in which participants were exposed to a set of pictures from the International Affective Picture System (IAPS) while their electrical brain activity was being recorded with an electroencephalogram (EEG). Participants described their feelings by choosing emotions from a list. Standard classification techniques confirmed the hypothesis that brainwave measures could significantly predict the AMIBEL ($\geq 82\%$ for each of the parameters which describe the AMIBEL). We discuss the prospects of improving the aptitudes of an Intelligent Tutoring System (ITS) by integrating a brain-sensing multi-agent system.

1 Previous Work

Research in education, psychology, computational linguistics, and artificial intelligence acknowledge that emotions have an effect on learning [3, 7]. Many works in that field focus on identifying learners' emotions as they interact with computer systems such as Intelligent Tutoring Systems [5] or educational games [4]. Unfortunately, many of these types of systems only focus on external behavior like face analysis, vocal tones and gesture recognition. Most of the time, psychological methods are used to collect real-time sensing data. Despite the advances in these methods, it is still a challenging problem. The effective emotional state and its assessment lack precision. In addition, these methods are not applicable in the case of disabled, taciturn and impassive learners. Today, researches are directed toward a multi-modal system that can automatically extract physiological signals changes in addition to vocal, facial or posture changes. All those features can be combined to detect and assess emotions. Our previous work [6, 7] indicated that an EEG is an efficient info source to detect emotions. Results show that the student's affect (Anger,

Boredom, Confusion, Contempt, Curious, Disgust, Eureka, and Frustration) can be accurately detected (82%) from brainwaves [6]. 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, with 73.55%, 74.86% and 75.16% for pleasure, arousal and dominance respectively [7]. Those results support the claim that all rating classes for the three emotional dimensions (pleasure, arousal and domination) can be automatically predicted with good accuracy through the nearest neighbor algorithm.

2 The Affective Model of Interplay between Emotions & Learning

To illustrate explicitly the link between emotions and learning, Kort, Reilly, and Picard (2001) proposed a comprehensive four-quadrant model called the Affective Model of Interplay between Emotions and Learning (AMIBEL). They also described the space of emotions it names. In fact, their model focuses only on the emotions commonly seen during learning. Some of them were noted in Figure 1.

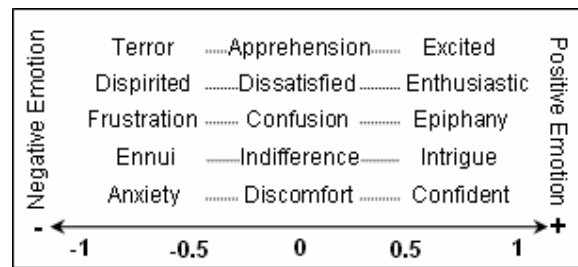


Fig. 1. Some emotions seen during Learning.

Figure 2 shows two perpendicular axes representing learning and emotion. It attempts to interweave the emotion axes shown in Figure 1 with the cognitive dynamics of the learning process. Learning axis is vertical; it ranges from Negative Learning (or Unlearning) at the bottom to Positive learning (or Constructive Learning) at the top. Emotion axis is horizontal, it could be one of the specific axes from Figure 1, or it could symbolize the n-vector of all relevant emotion axes (thus allowing multi-dimensional combinations of emotions). The positive valence (more pleasurable) emotions are on the right; the negative valence (more unpleasant) emotions are on the left. Learning is considered to be a set of packages containing worlds' knowledge, such as stereotypes, scripts, frames and other categories of generic knowledge. When learning is positive, it is incorporated to a schema which is a conceptual framework used to interpret incoming information, otherwise, in the case of negative learning, misconceptions are hopefully identified and removed from the schemas [1] as it occurs in case based reasoning. The Emotion axis ranges from negative emotion on the left to positive emotion on the right. According to this model, learners can transit among four different states, which are illustrated by the four

quadrants. That change follows complex dynamic mechanisms and not a rigid or linear sequence.

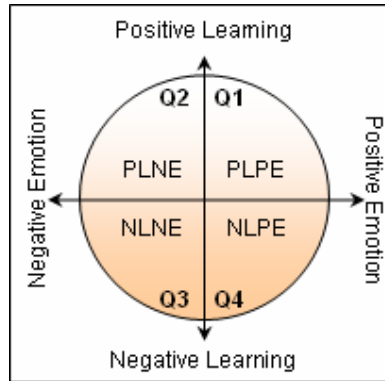


Fig. 2. The AMIBEL (Kort et al 2001)

Table 1 shows the repartition of some of the emotions cited on figure 1 among the four quadrants of figure 2. A learner usually begins in Quadrant Q1 or Q2. That is, he might be curious and fascinated about what he is learning (Q1) or he might be puzzled or bewildered and motivated to reduce confusion (Q2). When a learner encounters some difficulties, he sees that his knowledge needs to be improved. He may move down into the lower half of the diagram (Q3) with negative valence emotions as, for example, frustration as he eliminates his misconceptions. As he consolidates his knowledge he may move through Quadrant Q4 (through fresh research) to a new idea (and eventually back to Quadrant Q1). This model is a theoretical model, but has not yet been supported by empirical data from human learners. That is why we suggest using brainwaves to predict the four quadrants of the AMIBEL.

Table 1. Emotion's Sets among the four Quadrants.

Quadrant	Learning		Emotions		Emotions Sets
	-	+	-	+	
Q1		PL		PE	Awe, Satisfaction, Curiosity
Q2		PL	NE		Disappointment, Puzzlement, Confusion
Q3	NL		NE		Frustration, Discard, Misconception
Q4	NL			PE	Hopefulness, Fresh research

3 Using Brainwaves to assess the AMIBEL

Each individual neuron in the human brain communicates by sending tiny electrochemical signals. When millions of neurons are activated, each contributing its small electrical current, they generate a signal that is strong enough to be detected by

an electroencephalogram (EEG) device. EEG is the neurophysiologic measurement of the electrical activity of the brain by recording from electrodes placed on the scalp. During the last few years, increasing computing power increases the capabilities for EEG applications. Complex wave analysis can be performed in real-time, and artificial intelligence techniques are improving the computer's ability to associate a particular learner's brain activity with a particular emotional or learning state. Commonly, Brainwaves are categorized into 4 different frequency bands, or types, known as delta, theta, alpha, and beta waves. Each of these wave types often correlates with different mental states. Table 2 lists the different bands and their associated mental states.

Table 2: 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
Beta (β)	+12 Hz	Relaxed focus, high alertness, agitation, anxiety

In the past, we conducted experimentations on predicting emotion's states and emotion's assessments from brainwaves [11, 12]. Results were promising, as explained in the following sections.

4 Experiment's Procedure and Data Treatment

We selected 17 undergraduates from the department of computer sciences at The University of Montréal. They were exposed to a set of pictures taken from the International Affective Picture System (IAPS) [8] while they were connected to an electroencephalogram called Pendant EEG. Each picture induces a particular emotion in the learner. This one indicates his emotional states by choosing a list of emotions from Table 1. When participants arrived in the lab, they were given an informal consent followed by a description on the material used in the experimentation, the electroencephalogram Pendant EEG. The participants were subsequently exposed to emotional stimuli induced by pictures from IAPS for approximately 15 to 20 minutes, during which they watched each picture for at least 10 seconds. For each picture, we presented a list of emotions indicated on figure 1. During the experimentation, the electrical brain activity of the participants was recorded. Participants were encouraged to express their emotions by choosing from the list at any moment when they watched the pictures. In this current study we define Qel-mental State (QelMS) as a component which links each mental state to a quadrant, an emotion valence and a learning valence.

$$QelMS = (w_{\delta}, w_{\theta}, w_{\alpha}, w_{\beta}, Q, eV, lV).$$

Where $(w_\delta, w_\theta, w_\alpha, w_\beta) \in \mathbb{N}^4$ are the four main amplitudes of the brainwaves and Q is the quadrant, $Q \in \{Q1, Q2, Q3, Q4\}$, eV is the emotion's valence, $eV \in \{positive, negative\}$ and IV is the learning's valence, $IV \in \{positive, negative\}$. The size of the sample we collected is 30581 records. Each of them represents a Qel-Mental State.

5 Classifying the AMIBEL's Parameters from Brainwaves

Determining the AMIBEL's parameters (quadrant, emotion's and learning valences) from brainwaves can be cast as a multi-class classification problem. The mapping function is:

$$f: QelMS = (w_\delta, w_\theta, w_\alpha, w_\beta) \rightarrow (Q, eV, IV)$$

To comparatively evaluate the performance of various standard classification techniques, we used the Waikato Environment for Knowledge Analysis (WEKA) [10] in an endeavor to detect the four quadrants. The data set consisted of 30581 samples over 4 quadrants (figure 3, diagram A), 2 valences (positive and negative) for each of learning and emotion (figure 3, diagram B). The classification algorithms tested were a nearest neighbor classifier, J48 decision trees, bagging predictor and a classification via regression with a decision stump as the base learner. Several other algorithms were used but few of them gave good results. Table 3 shows the overall classification results using k-fold cross-validation5 (k = 10) for the various classifiers when evaluated on the data consisting of the quadrant, the emotion's valence and the learning's valence. 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. Classification accuracy varies from 65.36% to 88.77%. Kappa statistic measures the proportion of agreement between two raters with correction for chance. It is fair for Classification via regression algorithm (from 0.34 to 0.51) but good for the other algorithms (Nearest Neighbor, J48 Decision tree and Bagging), it varies between 0.60 and 0.76. In fact, 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. Results are shown in table 3. The nearest neighbor and bagging techniques provided the highest accuracy for each of the three outputs: quadrant, emotion's and learning's valences (\cong 81% for Quadrant and \cong 87% for emotion's and learning's valences). These two techniques yielded, globally a good kappa value (from .72 to .76), which is a good result. While the classification accuracies and kappa scores for the various classification algorithms are useful in obtaining an overview of the reliability of detecting the AMIBEL's parameters: quadrant, emotion's and learning's valences from brainwaves features, they do not provide any insight on class level accuracies.

Table 3: Comparison of classification techniques results

Algorithm	Classification Accuracy % (kappa statistic)		
	Quadrant	Emotion Val.	Learning Val.
Nearest Neighbor	82.52 (0.76)	88.77 (0.75)	87.67 (0.75)
J48 Decision tree	75.74 (0.66)	82.96 (0.61)	80.08 (0.60)
Bagging	80.77 (0.73)	87.87 (0.72)	86.26 (0.73)
Classification via regression	65.36 (0.51)	76.00 (0.41)	67.40 (0.34)

Table 4 lists the precision, recall, and F-measure scores as metrics for assessing class level accuracy for these 3 outputs, Table 4.(A) for Q and Table 4.(B) for eV and IV). Precision (specificity) and recall (sensitivity) are standard metrics for assessing the discriminability of a given class. The precision for class C is the proportion of samples that truly belong to class C among all the samples that were classified as class C. The recall score (sensitivity or true positive rate) provides a measure of the accuracy of the learning scheme in detecting a particular class. Finally, the F-measure provides a single metric of performance by combining the precision and recall.

Table 4: Detailed accuracies of the Nearest Neighbor algorithm for the outputs Q: Quadrant, eV: Emotion’s Valence and IV: Learning’s Valence

(A)

Rating classes	Precision	Recall	F-Measure
Q1	0.82	0.84	0.83
Q2	0.82	0.79	0.80
Q3	0.80	0.78	0.79
Q4	0.85	0.85	0.85

(B)

Rating classes	Accuracy Measures (eV, IV)					
	Precision		Recall		F-Measure	
	eV	IV	eV	IV	eV	IV
Positive	0.91	0.87	0.92	0.89	0.92	0.88
Negative	0.84	0.88	0.83	0.87	0.83	0.87

Results in table 4 indicate that the precision for the whole different rating classes were highly similar (it varies from .80 to .91). Recall is globally high among the different rating classes (from .78 to .92).

To give more weight to the rating classes with minority instances, we decided to use, for each of the three parameters Quadrant, Emotion’s and Learning’s Valences the Youden’s J-index [9] defined as:

$$JIndex = Card(RC)^{-1} \sum_{e \in RC} Precision_e$$

Where $Card(RC)$ is the cardinality of rating classes list. It is 4 in the case of quadrant and 2 in the case of emotion’s valence and learning valence. Through the

nearest neighbor algorithm, the values of $JIndex(Q, eV, IV)$ for: quadrant, emotion's valence and learning's valence are respectively 82.3%, 87.5% and 87.5% (calculated from table 4: A and B). They are close to our classification prediction shown in table 3 through the same algorithm (82.52%, 88.77% and 87.67%). These results support the claim that all rating classes for the three outputs can be automatically detected with good accuracy through the nearest neighbor algorithm.

6 Integration to a Multi-Agent System

In a previous work, a multi-agent system (MAS) was conceived to inform an ITS about the learner's emotional state [6] and assessment [7] from brainwaves. This MAS contains two agents: Emomental Agent which predicts the emotional states and the PAD-Mental Agent which predicts the emotion's assessment. Via the JADE (Java Agent Development Framework) platform [2] and according to the communication language FIPA-ACL, the emomental agent communicates with the planner located in the tutoring module of an ITS. In order to address the larger goal of extending an ITS into a more precise brainwave-sensing ITS, we added the thirs new agent we call Qel-Mental Agent (figure 3). The major advantages of using brainwaves for emotional dimensions detection lie in its effectiveness when used in the case of disabled, impassible or taciturn learners.

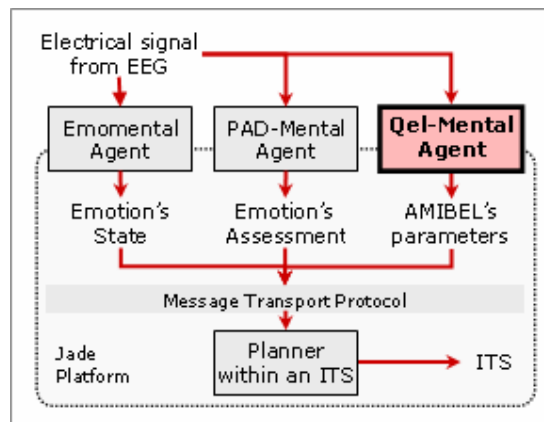


Fig. 3. Communication between Emomental Agent, PAD Agent, Qel-Agent and an Intelligent Tutoring System

Conclusion

This study has proven that the use of an electroencephalogram to measure the learners' brain wave activity is useful for predicting efficiently the AMIBEL's parameters which are: quadrant (Q), emotion's valence (eV) and learning's valence (IV). Prediction's Results are respectively 82.52%, 88.77% and 87.67%. This procedure allowed us to record the brainwaves of the learners exposed to emotional stimuli which seem occurring during learning. The major advantages of using brainwaves for predicting AMIBEL's parameters lie in its effectiveness when used in the case of disabled, impassible or taciturn learners. If the grounding criterion hypothesis holds in future replication, then it would give indications on how to help those learners to control the quality of their learning. We acknowledge that the use of EEG has some potential limitations. Any physical learner's movement can cause noise that is detected by the electrodes and interpreted as brain activity by Pendant EEG. Nevertheless, we think that the instructions given to participants (to remain steady), the number of participants (17) and the database size (30581 records) can considerably reduce this eventual noise. It appears that there are significant relationships between the brainwaves features and the AMIBEL's parameters. If the method described above proves to be effective, we can direct our focus to a second stage. An ITS would select an adequate pedagogical strategy that adapt to certain learner's precise mental, learning and emotional states.

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