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Predicting the Three Major Dimensions of the Learner's Emotions from Brainwaves

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***Abstract*—**This paper investigates how the use of machine learning techniques can significantly predict the three major dimensions of learner's emotions (pleasure, arousal and dominance) 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 recorded with an electroencephalogram (EEG). The pictures were already rated in a previous study via the affective rating system Self-Assessment Manikin (SAM) to assess the three dimensions of pleasure, arousal, and dominance. For each picture, we took the mean of these values for all subjects used in this previous study and associated them to the recorded brainwaves of the participants in our study. Correlation and regression analyses confirmed the hypothesis that brainwave measures could significantly predict emotional dimensions. This can be very useful in the case of impassive, taciturn or disabled learners. Standard classification techniques were used to assess the reliability of the automatic detection of learners' three major dimensions from the brainwaves. We discuss the results and the pertinence of such a method to assess learner's emotions and integrate it into a brainwave-sensing Intelligent Tutoring System.

***Keywords*—**Algorithms, Brainwaves, Emotional dimensions, Performance.

I. Introduction

EMOTIONS are a fundamental component of learning [30] and an important source of motivation [15][26][31]. During the last few years, much of the research in education, psychology, computational linguistics, and artificial intelligence has focused on the link between emotions and learning [5][10][19][22][24][23][12][27][33]. This interest comes from the user's modeling area. Often, the identification of the user's emotions is done as he/she interacts with computer systems such as tutoring systems or educational games [8][9]. Unfortunately, many of these types of systems only focus on external behavior like face analysis [13], vocal tones [11] 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 (how can we detect emotions in these cases?). Today, researches are directed towards a multi-modal system that can automatically extract non-verbal behaviors and features from face, postures and physiological changes, which can be used to detect and assess emotions.

Our previous works indicated that the use of an electroencephalogram to detect emotions in learning environments in the case of disabled learners is an efficient information source. Results show that the student's affect (Anger, Boredom, Confusion, Contempt, Curious, Disgust, Eureka, and Frustration) can be accurately detected (82%) from brainwaves [18]. However, we did not explore the link between brainwaves and emotional assessment. The present research investigates the assessment of emotions that arise during learning by measuring learner's brainwaves. The first goal of the present study is to assess the three major dimensions of emotions that occur frequently during learning. These three dimensions are: pleasure, arousal, and dominance. The second goal is to correlate brainwaves with these three major dimensions. An alternative refinement was to apply multiple regression techniques to assess which of the three dimensions can be predicted from brainwaves. The third goal is to apply various classification algorithms for improving automatic detection of the learner's three dimensions of emotions, from the brainwaves.

II. Brainwaves and Emotions

A. Brainwaves Measurement

In the human brain, each individual neuron communicates with the others by sending tiny electrochemical signals. When millions of neurons are activated, each contributing with small electrical current, they generate a signal that is strong enough to be detected by an electroencephalogram (EEG) device [7][3]. The EEG used in this experimentation is Pendant EEG. 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 I lists the different bands and their associated mental states.

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TABLE I
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

B. *Emotional Assessments*

Variance in emotional assessments were accounted for by three major dimensions: affective valence (varying from pleasant to unpleasant), arousal (varying from calm to excited) and dominance (or control) [35][25][32]. To assess the three dimensions of pleasure, arousal or dominance, we use the Self-Assessment Manikin (SAM) method, an affective rating system devised by Lang (1980). In this system, a graphic figure depicting values along each of the 3 dimensions on a continuously varying scale is used to indicate emotional reactions (Fig. 1).

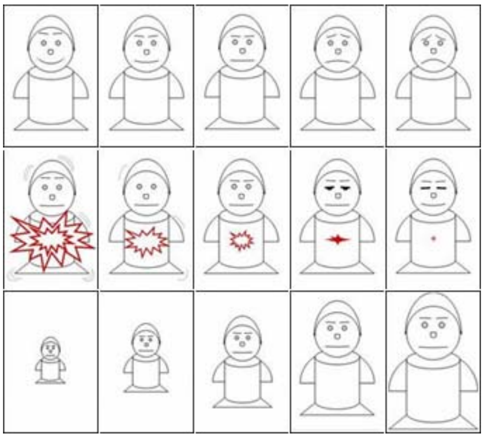

Fig. 1 Self-Assessment Manikin System

For the pleasure dimension, SAM ranges from a smiling, happy figure to a frowning, unhappy figure. For the arousal dimension, SAM ranges from an excited, wide-eyed figure to a relaxed, sleepy figure. For the dominance dimension, SAM ranges from a small figure (dominated) to a large figure (in control). Ratings are scored such that 9 represents a high rating on each dimension and 1 represents a low rating on each dimension.

C. *Previous Work*

In a previous study, we used brainwaves to predict emotional states during a learning experience 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% [18]. It appeared that there were significant relationships between brainwaves and emotional states experienced during learning. Participants were given a list of eight affective states along with definitions. The list of affective states consisted of anger, boredom, confusion, contempt, curious, disgust, eureka, and frustration. We defined an emomental state as follows:

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

Where $(w_\delta, w_\theta, w_\alpha, w_\beta) \in N^4$ are the four main amplitudes of the brainwaves and e is the emotional state from the finite list of the eight affective states defined above.

III. STUDY METHODOLOGY

The participants involved in this study consisted of 17 undergraduate students. They were selected from the department of computer sciences at University of Montréal. Participants were exposed to a set of pictures from the IAPS (a database of affective rated pictures) while they were connected to an electroencephalogram called Pendant EEG. Each picture was already rated via SAM in a previous study conducted by Lang (2005) where approximately 100 participants (half female) rated each picture [21]. From this normative rating procedure, we obtained the mean value of pleasure, arousal and dominance relative to each picture for all subjects and associated them with the brainwaves recorded for each participant.

A. *Experimentation Procedure*

When participants arrived in the lab, they were given a text explaining the experience (subject to their acceptance) 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 30 seconds. For each picture, we presented the SAM rating recorded in the study of Lang (2005). During the experimentation, the electrical brain activity of the participants was recorded. Fig. 2 shows the overall architecture of the data collection system.

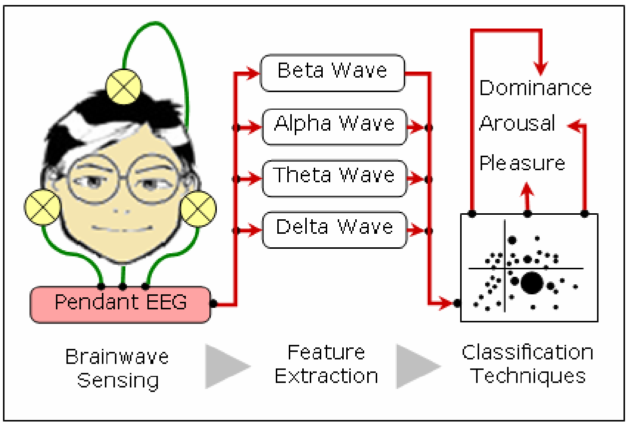

Fig. 2 The Overall Architecture

Participants were encouraged to modify the suggested SAM rating. Changes were not significant. Most of our participants agreed with the rating of Lang's previous results.

B. Data Treatment

In this current study we define a PAD-Emomental State as a component which links each emomental state to the three major emotional dimensions.

$$PAD\_EmS = \left(w_\delta, w_\theta, w_\alpha, w_\beta, e, P, A, D\right)$$

The component (P, A, D) contains 3 emotional dimensions: respectively pleasure, arousal and dominance.

The size of the sample we collected is 31599 records. Each of them represents a PAD-Emomental State. The amplitudes $\left(w_\delta, w_\theta, w_\alpha, w_\beta\right)$ 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 $n = 31599 \times 4$ is the size of our database collected multiplied by the four types of brainwaves. Pleasure, arousal and dominance values are continuous and vary from 1 to 9. For each dimension, we want to obtain a finite number of classes. We rounded each value $v \in (P, A, D)$ to the nearest value greater or equal to the one of the 17 discrete values. $rd(v \in [1..9]) \rightarrow v' \in \{1, 1.5, 2, 2.5, ..., 8.5, 9\}$. Table II shows the frequencies and the percentage of observations with the three major emotions as a function of rating classes.

TABLE II
PERCENTAGES OF OBSERVATIONS WITH THE THREE MAJOR EMOTIONS AS A FUNCTION OF RATING CLASSES

Rating classes	Rating frequencies, Percentage (on 31599)					
	Pleasure (p)		Arousal (a)		Dominance (d)	
{1, 1.5}	1349	04%	71	01%	--	--
{2, 2.5}	4528	14%	1825	06%	778	02%
{3, 3.5}	4393	15%	5345	17%	5519	17%
{4, 4.5}	3546	11%	8479	26%	5779	19%
{5, 5.5}	5458	17%	9893	31%	11124	35%
{6, 6.5}	6292	20%	5412	17%	8018	26%
{7, 7.5}	5523	17%	574	02%	381	01%
{8, 8.5, 9 }	510	02%	--	--	--	--

Due to a low frequency of observations, the classes {1, 1.5} (p = 4%; a=1%; d=0%) and {8, 8.5, 9} (p=2%; a=0%; d=0%) were not included in the subsequent analyses. This data cleaning procedure yielded to more reliable data for the rating classes 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6, 6.5, 7 and 7.5.

This resulted in a further reduction in the database from 31599 to 29740 for pleasure dimension with 4528 instances of {2, 2.5}-classes, 4393 of {3, 3.5}-classes, 3546 of {4, 4.5}-classes, 5458 of {5, 5.5}-classes, 6292 of {6, 6.5}-classes and 5523 of {7, 7.5}-classes. For arousal, the same database was reduced to 31528 with 1825 instances of {2, 2.5}-classes, 5345 of {3, 3.5}-classes, 8479 of {4, 4.5}-classes, 9893 of {5, 5.5}-classes, 5412 of {6, 6.5}-classes and 574 of {7, 7.5}-classes. For dominance, the database size remained the same, all pictures seen by participants was rated between 2 and 7.5; 31599 with 778 instances of {2, 2.5}-classes, 5519 of {3, 3.5}-classes, 5779 of {4, 4.5}-classes, 11124 of {5, 5.5}-classes, 8018 of {6, 6.5}-classes and 381 of {7, 7.5}-classes.

We observe that frequencies are concentrated between 2nd and the 7th rating classes.

IV. RESULTS

The data (brainwaves amplitudes) were collected continuously from the Pendant EEG. They were then correlated with each of the three dimensions of emotions expressed by the participant: pleasure, arousal and dominance. Preliminary analyses revealed significant correlations for all the three dimensions.

A. Correlations between Brainwaves and the Three Major Emotional Dimensions

TABLE III
CORRELATIONS BETWEEN BRAINWAVES AND PLEASURE, AROUSAL AND DOMINANCE

Brainwaves	Pleasure	Arousal	Dominance
Delta	-,026**	-,005	-,024**
Theta	-,006	,035**	-,031**
Alpha	,005	-,037**	,015**
Beta	-,041**	,026**	-,055**

* significant at p<,05. ** significant at p< ,01

Spearman correlations are presented in Table III in a 4 by 3 matrix. Spearman Rank Correlation measures the correlation between two sequences of values. The two sequences are ranked separately and the differences in rank are calculated at each position. Each of the brainwaves features predicted one or more of the three major emotional dimensions and there were some variations among the emotional dimensions.

Knowing the high degree of freedom (31597=31599-2), all of the brainwaves features showed a weak but a significant correlation with dominance. Delta brainwave had a negative correlation with pleasure and dominance. Theta brainwave showed a positive correlation with arousal but a negative correlation with dominance. Alpha brainwave also had a weak but significant negative correlation with arousal and positive with dominance. Beta correlated with all three major dimensions, positively with arousal and negatively with pleasure and dominance.

B. Predicting Emotional Dimensions from Brainwaves

Multiple machine learning techniques were performed, one for each of the three emotional dimensions, with the four brainwave features as predictors. Significant overall relationships were found for all three emotional dimensions: pleasure, arousal and dominance. p < .05 was adopted in all subsequent statistical tests.

1) Pleasure

Multiple regression analysis results were interesting for the following observations: The ANOVA table reports a significant F-statistic = 21.67 (p=0.000), indicating that using the model is better than guessing the mean, with β-weights of -0.014, -0.007, 0.012 and -0.048 for brainwaves delta, theta, alpha and beta respectively (see Table IV). Only 0.3% of the variation in pleasure is explained by the model (R2adj = 0.003). Beta brainwave feature was statistically significant, but not delta brainwave.

TABLE IV
COEFFICIENT OF THE REGRESSION LINE TO PREDICT PLEASURE DIMENSION FROM THE FOUR BRAINWAVES

Model	Unstandardized		Standard. Coeff.	t	Sig.
	B	Std. Error	beta		
Constant	4.99	0.026		193.967	0.000
Delta	-0.041	0.017	-0.014	-2.416	0.016
Theta	-0.022	0.017	-0.007	-1.314	0.189
Alpha	0.033	0.016	0.012	2.041	0.041
Beta	-0.122	0.014	-0.048	-8.424	0.000

Theta brainwave does not contribute much to the model (p=0.189) while Beta Brainwave contributes more to the model with a largest absolute standardized coefficient |-0.048|.

2) Arousal

Multiple regression analysis results were interesting for the following observations: The ANOVA table reports a significant F-statistic = 44.16 (p=0.000), indicating that using the model is better than guessing the mean, with β-weights of -0.018, 0.110, -0.082 and 0.033 for delta, theta, alpha and beta brainwaves, respectively (see Table V). Only of 0.5% the variation in arousal is explained by the model (R2adj = 0.005). Brainwaves beta, alpha and theta feature were statistically significant, but not brainwave delta.

TABLE V
COEFFICIENT OF THE REGRESSION LINE TO PREDICT AROUSAL DIMENSION FROM THE FOUR BRAINWAVES

Model	Unstandardized		Standard. Coeff.	t	Sig.
	B	Std. Error	beta		
Constant	4.63	0.016		284.401	0.000
Delta	-0.08	0.011	-0.009	-1.657	0.097
Theta	0.110	0.011	0.059	10.438	0.000
Alpha	-0.082	0.010	-0.045	-7.925	0.000
Beta	0.033	0.009	0.020	3.601	0.000

The two largest absolute standardized coefficients are |0.059| and |-0.045| which means that respectively Theta and Alpha Brainwaves contribute more to the model than the other brainwaves.

3) Dominance

Multiple regression analysis results were interesting for the following observations: The ANOVA table reports a significant F-statistic = 36.67 (p=0.000), indicating that using the model is better than guessing the mean, with β-weights of -0.020, -0.040, 0.046 and -0.086 for delta, theta, alpha and beta brainwaves, respectively (see Table VI). Only 0.3% of the variation in pleasure is explained by the model (R2adj = 0.003). Beta brainwave feature was statistically significant, but not delta brainwave.

TABLE VI
COEFFICIENT OF THE REGRESSION LINE TO PREDICT DOMINANCE DIMENSION FROM THE FOUR BRAINWAVES

Model	Unstandardized		Standard. Coeff.	t	Sig.
	B	Std. Error	beta		
Constant	5.01	0.015		326.529	0.000
Delta	-0.020	0.010	-0.012	-2.033	0.042
Theta	-0.040	0.010	-0.023	-4.008	0.000
Alpha	0.046	0.010	0.027	4.728	0.000
Beta	-0.086	0.009	-0.057	-10.036	0.000

Theta brainwave does not contribute much to the model (p=0.189) while Beta Brainwave contributes more to the model with a largest absolute standardized coefficient |-0.048|.

C. Classifying Emotional Dimensions from Brainwaves

Determining the three emotional dimensions from brainwaves can be cast as a multi-class classification problem. The mapping function is:

$$f : PAD - EmS = \left(w_{\delta}, w_{\theta}, w_{\alpha}, w_{\beta}\right) \rightarrow (P, A, D)$$

The multiple regression analyses presented in the previous section produced significant models for all three emotional dimensions: pleasure, arousal and dominance. In our previous work, we conceived the emomental agent [18]. This agent informs an ITS about the learner's emotional state predicted from his brainwaves. Via the JADE (Java Agent Development Framework) platform [4] and according to the communication language FIPA-ACL, the emomental agent communicates with the planner located in the tutoring module of an ITS. It sends to the latter the predicted emotional state (Fig. 3).

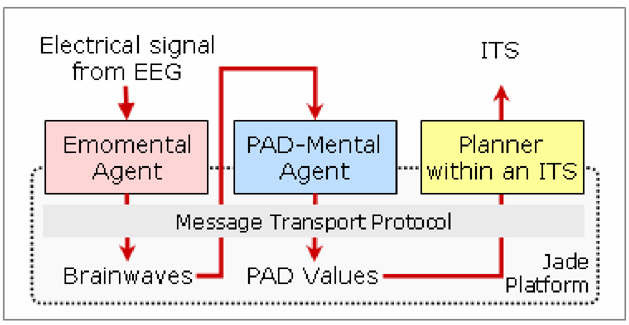

Fig. 3 Communication between Emomental Agent, PAD Agent and an Intelligent Tutoring System

In order to address the larger goal of extending an ITS into a more precise brainwave-sensing ITS, we implemented another agent called PAD-Mental Agent. Therefore, we present some preliminary results on automatic detection of the learner's three emotional dimensions from the brainwave features recorded by an EEG. 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.

To comparatively evaluate the performance of various standard classification techniques, we used the Waikato Environment for Knowledge Analysis (WEKA) [34] in an endeavor to detect pleasure, arousal and dominance dimensions from brainwaves. The data set consisted of 29740 samples of pleasure, 31528 of arousal, and 31599 of dominance distributed over 15 classes as shown in table II. The classification algorithms tested were a nearest neighbor classifier [1], J48 decision trees [28], bagging predictor [6] and a classification via regression [14][2][16][17] with a decision stump as the base learner. Several other algorithms were used but few of them gave good results. Table 4 shows the overall classification results using k-fold cross-validation5 (k = 10) for the various classifiers when evaluated on the data consisting of the four brainwaves features for the emotional dimensions pleasure, arousal and dominance. 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 pleasure, arousal and dominance. Classification accuracy varies from 58.54% to 75.16%. Kappa statistic measures the proportion of agreement between two raters with correction for chance. It is fair for the Classification via regression algorithm (≅ 0.53) but good for the other algorithms (Nearest Neighbor, J48 Decision tree and Bagging), it varies between 0.64 and 0.72. 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 [29]. Results are shown on Table VII.

TABLE VII
COMPARISON OF CLASSIFICATION TECHNIQUES RESULTS

Algorithm	Classification Accuracy % (kappa statistic)		
	Pleasure	Arousal	Dominance
Nearest Neighbor	73.55 (0.71)	74.86 (0.72)	75.16 (0.71)
J48 Decision tree	66.33 (0.64)	68.51 (0.64)	68.92 (0.64)
Bagging	74.66 (0.72)	74.79 (0.71)	75.29 (0.71)
Classification via regression	59.01 (0.55)	58.54 (0.53)	58.93 (0.52)

The nearest neighbor and bagging techniques provided the highest accuracy for each of the three emotional dimensions (≅ 74% for pleasure and arousal and ≅ 75% for dominance). These two techniques yielded, globally the same kappa value (≅ .71), 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 three major emotional dimensions from brainwaves features, they do not provide any insight on class level accuracies. Table VIII lists the precision, recall, and F-measure scores as metrics for assessing class level accuracy for the three major emotional dimensions: pleasure, arousal and dominance. 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. Figure 4 gives details of precision by classes. 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.

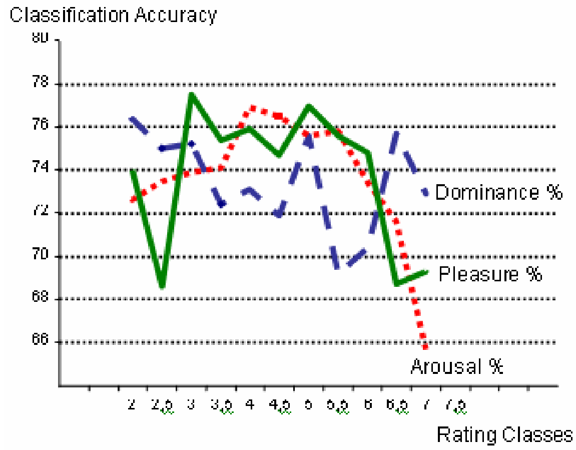

Fig. 4 Accuracies by class in the case of Nearest Neighbor Algorithm for the three emotional dimensions

TABLE VIII
COMPARISON OF CLASSIFICATION TECHNIQUES RESULTS

Classes	Precision			Recall			F-Mesure		
	P	A	D	P	A	D	P	A	D
2	0.74	0.71	0.71	0.77	0.73	0.74	0.75	0.72	0.73
2.5	0.73	0.70	0.63	0.75	0.74	0.69	0.74	0.72	0.66
3	0.74	0.71	0.74	0.75	0.74	0.78	0.75	0.72	0.76
3.5	0.71	0.72	0.74	0.72	0.74	0.75	0.72	0.73	0.75
4	0.72	0.76	0.74	0.73	0.77	0.76	0.72	0.76	0.75
4.5	0.72	0.77	0.74	0.72	0.77	0.75	0.72	0.77	0.74
5	0.75	0.76	0.77	0.76	0.76	0.77	0.75	0.76	0.77
5.5	0.69	0.78	0.77	0.69	0.76	0.76	0.69	0.77	0.76
6	0.73	0.76	0.77	0.70	0.73	0.75	0.72	0.75	0.76
6.5	0.78	0.74	0.72	0.76	0.72	0.69	0.77	0.73	0.70
7	0.75	0.69	0.72	0.73	0.66	0.69	0.74	0.67	0.71
7.5	0.76	--	0.83	0.72	--	0.79	0.74	--	0.81

Table VIII indicates that the precision for the whole different rating classes were highly similar (varies between 0.69 and 0.83). It also shows that the recall is globally similar among the different class rating (between 0.66 and 0.79). We also see that the F-measure for the different rating classes are quantitative similar.

To give more weight to the rating classes with minority instances, we decided to use, for each of Pleasure, arousal and dominance the Youden's J-index [36] defined as:

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

Where $Card(RC)$ is the cardinality of rating classes list. It is 12 in case of pleasure and dominance and 11 in case of arousal. Through the nearest neighbor algorithm, the values of $JIndex(P, A, D)$ for: pleasure, arousal and dominance are respectively 73.5%, 74.6% and 74%. They are close to our classification prediction shown in table VII through the same algorithm (73.55%, 74.86% and 75.16%). These results support the claim that all rating classes for the three emotional dimensions can be automatically detected with good accuracy through the nearest neighbor algorithm.

V. Discussion

This study has proven that the use of electroencephalogram to measure learners' brain wave activity is useful for assessing emotions by the three major emotional dimensions. This procedure allowed us to record the brainwaves of learners exposed to emotional stimuli that can occur during learning. These data were used to predict pleasure, arousal and dominance values according to the SAM scale.

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. If the grounding criterion hypothesis holds in future replication, then it would give indications on how to help those learners to control their emotions for a better interaction between emotions and 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 the Pendant EEG. Nevertheless, we think that instructions given to participants (to remain very steady), the number of participants (17) and the database size (31599 records) can considerably reduce this eventual noise.

Five rating classes were removed from the analysis due to the low frequency of observations. These were the extreme values on SAM scale: {1, 1.5, 8, 8.5, 9}.

It appears that there are significant relationships between the brainwaves features and the three major emotional dimensions that we considered.

The multiple regression analyses resulted in accurate predictions for pleasure, arousal and dominance degrees. Delta brainwave showed a significant negative correlation with pleasure and dominance. Theta and Beta brainwaves showed a significant negative correlation with pleasure and dominance (highly negative for beta) but a positive correlation with arousal (strong positive for Theta). Alpha brainwave had a significant negative correlation with arousal and dominance.

If the method described above proves to be effective in identifying the learner's three emotional dimensions emotions, we can direct our focus to a second stage. An ITS would select an adequate pedagogical strategy that adapt to certain learner's emotional dimensions in addition to cognitive states. This adaptation would increase the bandwidth of communication and allow an ITS to respond at a better level.

VI. Acknowledgment

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