Arguedas, M. [et al.] (2016) A fuzzy-based approach for classifying students' emotional states in online collaborative work. *2016 10th International Conference on Complex, Intelligent, and Software Intensive Systems, CISIS 2016, Fukuoka Institute of Technology (FIT), Fukuoka, Japan 6-8 July 2016: proceedings*. IEEE. Pp. 61-68. Doi: http://dx.doi.org/10.1109/CISIS.2016.141.

Arguedas, M. [et al.] (2016) A fuzzy-based approach for classifying students' emotional states in online collaborative work. *2016 10th International Conference on Complex, Intelligent, and Software Intensive Systems, CISIS 2016, Fukuoka Institute of Technology (FIT), Fukuoka, Japan 6-8 July 2016: proceedings*. IEEE. Pp. 61-68. Doi: http://dx.doi.org/10.1109/CISIS.2016.141.

A Fuzzy-based Approach for Classifying Students' Emotional States in Online Collaborative Work

Marta Arguedas[1]
martaarg2@gmail.com

Luis Casillas[2]
luis.casillas@cucei.udg.mx

Fatos Xhafa[3]
fatos.xhafa@gmail.com

Thanasis Daradoumis[1, 4]
adaradoumis@uoc.edu

AdrianaPeña[2]
adriana.pena@cucei.udg.mx

Santi Caballé[1]
scaballe@uoc.edu

[1]Department of Computer Science, Multimedia and Telecommunications
Open University of Catalonia
Barcelona, Spain

[2]Department of Computer Science
University of Guadalajara
Guadalajara, Mexico

[3]Department of Computer Science,
Technical University of Catalonia
SmartLearn Research Group, Open University of Catalonia
Barcelona, Spain

[4]Department of Cultural Technology and Communication (D.C.T.C), School of Social Sciences
University of Aegean
Mytilini, Greece

***Abstract* — Emotion awareness is becoming a key aspect in collaborative work at academia, enterprises and organizations that use collaborative group work in their activity. Due to pervasiveness of ICT's, most of collaboration can be performed through communication media channels such as discussion forums, social networks, etc. The emotive state of the users while they carry out their activity such as collaborative learning at Universities or project work at enterprises and organizations influences very much their performance and can actually determine the final learning or project outcome. Therefore, monitoring the users' emotive states and using that information for providing feedback and scaffolding is crucial. To this end, automated analysis over data collected from communication channels is a useful source. In this paper, we propose an approach to process such collected data in order to classify and assess emotional states of involved users and provide them feedback accordingly to their emotive states. In order to achieve this, a fuzzy approach is used to build the emotive classification system, which is fed with data from ANEW dictionary, whose words are bound to emotional weights and these, in turn, are used to map Fuzzy sets in our proposal. The proposed fuzzy-based system has been evaluated using real data from collaborative learning courses in an academic context.**

Keywords— Emotion Awareness, Fuzzy Clasification, Collaborative Learning, Automated Emotional Assessment.

I. INTRODUCTION

Our research work aims at investigating the effectiveness of the emotion labeling model to detect emotions in educational discourse (text and conversation) in a non-intrusive way making emotion awareness explicit both at individual and group level [1]. Studies have shown that emotional experiences influence student's motivation, learning strategies and achievement whereas such emotional experiences are influenced by personality and classroom characteristics [2][3].

Given that people are able to express a wide range of emotions, which vary in intensity, duration, context, etc. during activity time our model is based on dimensional categories of emotions [4]. It also makes use of affective dictionaries expressing the emotional weights of words as a function of affective dimensions (pleasure, arousal, etc.). Each of these dimensions is preprocessed to obtain fuzzy values corresponding to the magnitudes of each emotional dimension.

Then, there is performed a conversion of the qualified emotional state defuzzified in discrete affective states to provide awareness emotion to both teachers and students. Thus, the aim of this study is to present an effective approach to label affective behavior in educational discourse based on fuzzy logic, which will enable a human (or virtual) tutor to capture students' emotions, make students aware of their own emotions, assess these emotions and provide appropriate feedback to involved actors. In order to address these challenges, this paper is organized as follows. In Section II, we present a comprehensive analysis of the state of the art of affective dictionaries in Sentiment Analysis field, dimensional models of emotion as well as of applications of fuzzy logic to the field of classification of emotional states.. Based on this analysis, in Section III, we present our proposal that explains how we address these issues. We describe our approach at a conceptual design level. In Section IV we give an application example of our model in real case setting. Finally, in Section V, we present the results obtained so far, concluding with future work in Section VI.

II. RELATED WORK

Our goal is to classify and later label the students' emotional state through the analysis of their educative discourse in a virtual learning environment. To that end, before starting the design of our model, we have extensively revised the literature related to three topics that concern its development.

First, we reviewed various existing models for the classification of the different emotional states. Secondly, we studied the different affective dictionaries that have been compiled so far, to identify how each one of them provides the use of information about the affective weights of words composing the educational discourse.

Finally, we checked the related works about the application of fuzzy logic in the Sentiment Analysis field

A. Emotion models

In Artificial Intelligence, affective computing is the branch of studies and developments systems and devices that can recognize, interpret, process, and simulate human affects, whose motivation is the ability to simulate empathy. The machine should interpret the emotional state of humans and adapt its behavior to them, giving an appropriate response to their emotions [5].

There are two leading models describing how humans perceive and classify emotion, namely, dimensional and categorical models [7], [8]. Categorical models classify emotions into *basic*, *secondary*, *tertiary*, etc. [11] [12] [13], while dimensional models specify gradual emotions as *arousal*, *valence*, *control*, *intensity*, *duration*, *frequency of occurrence*, etc. [14], [16], [17] and [19].

Emotions can be used in the learning context to increase student's attention as well as to improve memory and reasoning [10]. In this context, tutors must be prepared to create affective learning situations and encourage collaborative knowledge construction and identify students' feelings that difficult the learning [9].

For instance, the PAD (Pleasure-Arousal-Dominance) emotional state model is a psychological model developed in [27] to describe and measure emotional states. PAD uses three numerical dimensions to represent all emotions. Its initial use was in a theory of environmental psychology, the core idea being that physical environments influence people through their emotional impact. The PA part of PAD was developed into a circumplex model of emotion experience, and those two dimensions were termed "core affect". The D part of PAD was re-conceptualized as part of the appraisal process in an emotional episode (a cold cognitive assessment of the situation eliciting the emotion). A more fully developed version of this approach is termed the psychological construction theory of emotion. The PAD model has been used to study nonverbal communication such as body language in psychology [29]. It has also been applied to the construction of animated characters that express emotions in virtual worlds [28].

Plutchick offers an integrative theory based on evolutionary principles [15]. Emotions are adaptive—in fact, they have a complexity born of a long evolutionary history—and although we conceive the emotions as feeling states. According to [15], the feeling state is part of a process involving both cognition and behavior and containing several feedback loops.

As mentioned before, our goal in this work is to develop tools that report teachers with useful information about students' emotional state, to assess these emotions and provide appropriate affective feedback to students. To this end, we choose a mixed model composed by three dimensions [27] and eight emotional labels [15].

B. Affective Dictionaries

In Sentiment Analysis field, textual information includes, among others, subjective expressions that describe people's sentiments, appraisals or feelings toward entities, events and their properties [6]. Within this area, some affective dictionaries have been developed and are widely used.

These dictionaries provide a lexical repository in different languages. In particular, we have carried out a wide review of affective dictionaries in Spanish language on both models.

SentiWordNet is a lexical resource for opinion mining [26]. SentiWordNet assigns to each synset of WordNet three sentiment scores: positivity, negativity and objectivity. The method we have used to develop SentiWordNet is an adaptation to synset classification of our method for deciding the PN-polarity and SOpolarity of terms. The method relies on training a set of ternary classifiers, each of them capable of deciding whether a synset is Positive, Negative, or Objective. However, SentiWordNet is not available in Spanish.

The development of the framework Affective Norms for English Words (ANEW [23]) is an instrument into the dimensional perspective of emotions based on works as [21] and [22]. From this perspective, three basic dimensions are proposed, through which the entire range of human emotions can be organized: valence (which ranges from pleasant to unpleasant), arousal (which ranges from calm to excite) and dominance or control (ranging from in control to out of control). The ANEW list provides normative values in these dimensions for 1,034 words and there is a Spanish adaptation of the ANEW made by [20].

Whissell's Dictionary of Affect in Language, originally designed to quantify the Pleasantness and Activation of specifically emotional words, was revised to increase its applicability to samples of natural language. A third rated dimension (Imagery) was added, and normative scores were obtained for natural English.

Evidence supports the reliability and validity of ratings. The revised Dictionary, which contains ratings for words characteristic of natural language, is a portable tool that can be applied in almost any situation involving language [24].

The NRC Emotion Lexicon (EmoLex) is a list of English words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive) [25]. The annotations were manually done by crowd sourcing.

Despite some cultural differences, it has been shown that a majority of affective norms are stable across languages. Given that three basic dimensions, namely, valence, arousal and dominance are commonly used by researchers we decided to use the Spanish version of ANEW dictionary merged with the Spanish version of EmoLex.

C. *Fuzzy Logic Applied to Sentiment Analysis*

Regarding fuzzy logic supporting the sentiment analysis, most of authors involved refer to [18], which focuses on the WordNet dictionary, in order to grasp some awareness from text mining from the sentiment analysis approach.

The authors were able to capture average behaviors shown by words, based on regular statistics analysis to build a fuzzy logic scheme aimed at producing a qualitative description for words; turning quantitative magnitudes into literal terms bound to qualitative perceptions, such as: good, bad, etc.

Our proposal is to produce similar scheme for word treatment [18]. Nevertheless, our study focuses on the ANEW and fuzzy qualifiers bound to amounts: few, regular, many. These qualifiers will be later on crossed over throughout specific inference rules.

These inference rules provide the support to explain as qualitative terms, the amounts achieved by indicators. Hence, high level emotions could be implied from plain numbers. Inspired by [19], our proposal is a fuzzy classifier, more precisely, a statistical classifier, which provides a priori a qualitative assessment to the amounts assigned by ANEW to every word.

The advantage of the statistical approach is to reduce the classical *pollution* problem of training and analyzing the scenario using the same dataset. Affective dictionaries have, usually, a limited number of words. Our statistical classifier uses centrality and dispersion measures calculated from the ANEW analysis dimensions. These measures are used to build the fuzzy classifier, as explained later in this paper.

III. OUR FUZZY APROACH

Our model is formed by a set of tools implemented in Java. These tools process the students-created texts through various steps (see Fig. 1). Once the process has finished, we obtain the synthetic opinion of the original message, from the point of view of the author's emotional and affective state.

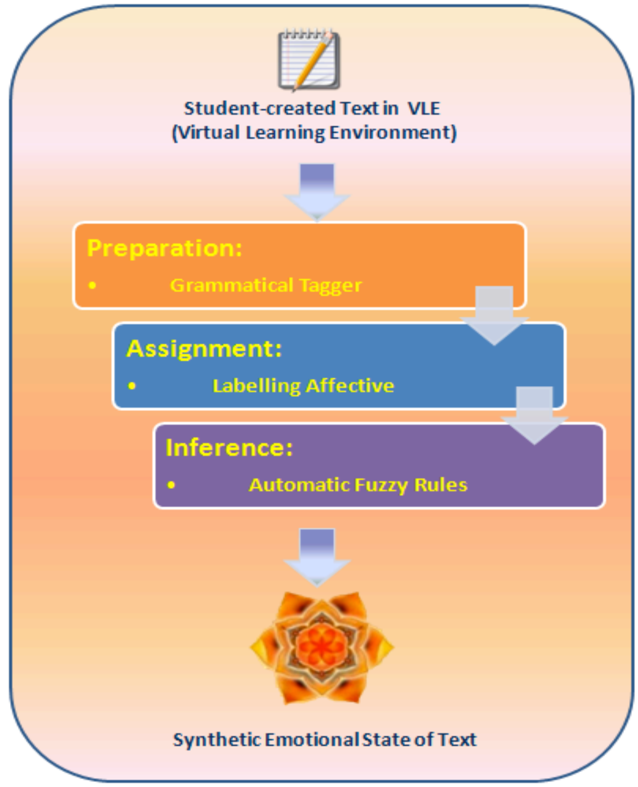


Figure 1. Proceses of Our Fuzzy Model Aproach

A. *Affective Dictionairies*

As mentioned in the previous section, there are different dictionaries and thesaurus that assign weights to each word for a certain group of dimensions and/or categories (DAL (Whisell Dictionary Of Affect), WordNet Affect, ANEW, etc.). Of these, in order to develop our tool, we took as a starting point ANEW Dictionary and NCR Emotion Lexicon.

Firstly, because of there are Spanish words' versions for each dictionary. Secondly, because the first dictionary (ANEW) scores each word assigning and affective weight based on a three dimensional emotional classification model: Pleasure, Arousal and Dominance. And, the other dictionary (NCR) affectively scores words as a combination of the primal emotions described in Plutchick's model. So EmoLex assigns a value from 0 to 1 to each of the emotional axis of Plutchick, if the word has an emotional weight in that axis. In order to use it in our model, we modified the original structure of the ANEW dictionary so we only use 4 columns (see Table 1).

In the table, the first column contains the words list of the Spanish dictionary and the rest of the columns contain the affective load of each word assigned to Pleasure, Arousal and Dominance, respectively.

Finally, the mean and standard deviation are calculated for each of the corresponding dimensions. Then, we match both dictionaries to obtain a new words combination with the words in common. Our resulting thesaurus was reduced to 822 words in Spanish. Using the dimensional and categorical information of the words' emotional load from a text, we aim at giving enough information to the teacher in order to determine the emotional state of the students during their work on the different tasks that form the learning activity in the virtual environments.

TABLE I. STRUCTURE OF OUR TESAURUS

	Dictionary ANEW			*Dictionary EMOLEX*							
Word	**Pleasure**	**Arousal**	**Dominance**	**Anger**	**Anticipation**	**Disgust**	**Fear**	**Joy**	**Sad**	**Surprise**	**Trust**
P_1	$V_{1.1}$	$V_{1.2}$	$V_{1.3}$	$V_{1.4}$	$V_{1.5}$	$V_{1.6}$	$V_{1.7}$	$V_{1.8}$	$V_{1.9}$	$V_{1.10}$	$V_{1.11}$
P_2	$V_{2.1}$	$V_{2.2}$	$V_{2.3}$	$V_{2.4}$	$V_{2.5}$	$V_{2.6}$	$V_{2.7}$	$V_{2.8}$	$V_{2.9}$	$V_{2.10}$	$V_{2.11}$
P_3	$V_{3.1}$	$V_{3.2}$	$V_{3.3}$	$V_{3.4}$	$V_{3.5}$	$V_{3.6}$	$V_{3.7}$	$V_{3.8}$	$V_{3.9}$	$V_{3.10}$	$V_{3.11}$
. . . .	. . . .	. . . .	. . . .	. . . .	. . . .	. . . .	. . . .	. . . .	. . . .	. . . .	. . . .
P_n	$V_{n.1}$	$V_{n.2}$	$V_{n.3}$	$V_{n.4}$	$V_{n.5}$	$V_{n.6}$	$V_{n.7}$	$V_{n.8}$	$V_{n.9}$	$V_{n.10}$	$V_{n.11}$
Mean	μ_1	μ_2	μ_3								
SD	σ_1	σ_2	σ_3								

B. *Fuzzy Classification*

An intelligent system (IS) needs to be able to evaluate the actual state of a phenomenon and act accordingly. In addition, such an IS needs a compact and discrete quantity of affective states to offer an efficient answer in a reasonable amount of time. In our case, it's needed that the teacher knows his/her students' emotional states as accurately as possible to give an effective affective feedback.

A fuzzy system (FS) allows us to process countless numerical values from a variable, mapping them in a practical discrete specter for the processing. That is to say, it allows us to conduct a qualitative evaluation from a magnitude, providing each value with a certain semantic. The most appealing characteristics of the fuzzy logic are its flexibility, its tolerance to imprecision, its capacity to model non-linear problems and its natural language base. In this case, the imprecision derives from the countless existent emotional states both clear and transitional that appears in ANEW dictionary's values, some are labeled but others are not.

The non-linearity happens because all this states are composed by various dimensions with different grades of magnitude, that aren't part of an arithmetic progression nor a geometrical one neither and exponential one. Their base in the natural language is due to the objective of detecting these affective states in the students' respective languages written texts in a virtual learning environment. Therefore, in order to conduct a qualitative evaluation of the words composing the texts, we set the base on an FS formed by a number of fuzzy groups that try to model the ambiguity of a perceived variable.

The theory of fuzzy or fuzzy sets was developed to the end of portraying mathematically the intrinsic imprecision of certain object categories. To determine the belonging to a certain group in the values range from a certain dimension we start from the Degree of Truth (DT).

The Degree of Truth is an element that belongs to a close interval between 0 and 1 but due to the interval belonging to the real numbers group, the Degree of Truth is infinite to the same manner that the number of a person's possible emotional states in a certain instant is infinite.

These fuzzy groups are obtained through the "membership functions". These functions determine the degree of belonging to a defined group by a qualitative label classifying the emotional state from a person or a group based on the emotional weight of the words used during their emotional discourse. The graphic representation of these functions may take various forms (trapezoidal, triangular, singleton, etc.) In our model, these functions take the form of an "S" as shown in Fig. 2.

The first step was to verify that the data had a normal distribution. We obtained the mean to get close to the values of the variable's area of interest, and then calculated the standard deviation to determine the thickness of the bell curves and the number of groups that the values are going to be divided into based on the qualitative values that will be used.

In this case, the qualitative values are three low, medium and high, so we will obtain three groups as shown in Fig. 2. We followed a series of steps to obtain the limits of each group as described next.

First, we calculated the percentage of deviation by formulae (1):

$$\%\sigma = \frac{\sigma * 100}{\mu} \tag{1}$$

Then, based on the number of group (numConjs=3) and applying the equations (2) and (3) we obtained the mean and standard deviation segments.

$$S\mu \left\{ \begin{array}{ll} \dfrac{(\mu * 2.0) * 0.5}{\text{numConjs}} & \%\sigma < 25 \\ \dfrac{(\mu * 2.0) * 0.8}{\text{numConjs}} & 25 \le \%\sigma < 50 \\ \dfrac{(\mu * 2.0) * 0.8}{\text{numConjs}} & \%\sigma \ge 50 \end{array} \right\} \tag{2}$$

$$S\sigma \left\{ \begin{array}{ll} \dfrac{\sigma * 1.8}{\text{numConjs}} & \%\sigma < 25 \\ \dfrac{\sigma * 1.2}{\text{numConjs}} & 25 \le \%\sigma < 50 \\ \dfrac{\sigma * 0.8}{\text{numConjs}} & \%\sigma \ge 50 \end{array} \right\} \tag{3}$$

Finally, we determined the centers, and the left and right limits that matched each group applying the equations (4).

$$\begin{array}{l} center = meanSegment * (i + 1) \\ leftLimit = (i = 0)?-1 : center - stdDevSegment * 2 \\ rightLimit = (i + 1 = numSets)?-1 + stdDevSegment * 2 \end{array} \tag{4}$$

The values resulting from applying these equations to each dimension magnitude from the ANEW dictionary are shown in Tables II, III and IV, respectively.

TABLE II. RESULTING VALUES FOR PLEASURE

*Variable Name: ***PLEASURE***	
Mean:	4.74
Standard Deviation (SD):	2.14
Percentage DS :	45.14767932489451
Segment size:	2.528
Curves' data of three groups built related to Pleasure	
Pleasure _Low :	**curveZ** C: 2.528 LD: 4.24
Pleasure _Medium :	**curvePi** LI: 3.344 C: 5.056 LD: 6.768
Pleasure _High:	**curveS** LI: 5.872 C: 7.584

TABLE III. RESULTING VALUES FOR AROUSAL

*Variable Name: ***AROUSAL***	
Mean:	5.53
Standard Deviation (SD):	1.0
Percentage DS :	18.083182640144663
Segment size:	1.8433333333333335
Curves' data of three groups built related to Arousal	
Arousal_Low :	**curveZ** C: 1.84333 LD: 3.04333
Arousal_Medium :	**curvePi** LI: 2.48666 C: 3.68666 LD:
Arousal_High:	**curveS** LI: 4.33 C: 5.53

TABLE IV. RESULTING VALUES FOR DOMINANCE

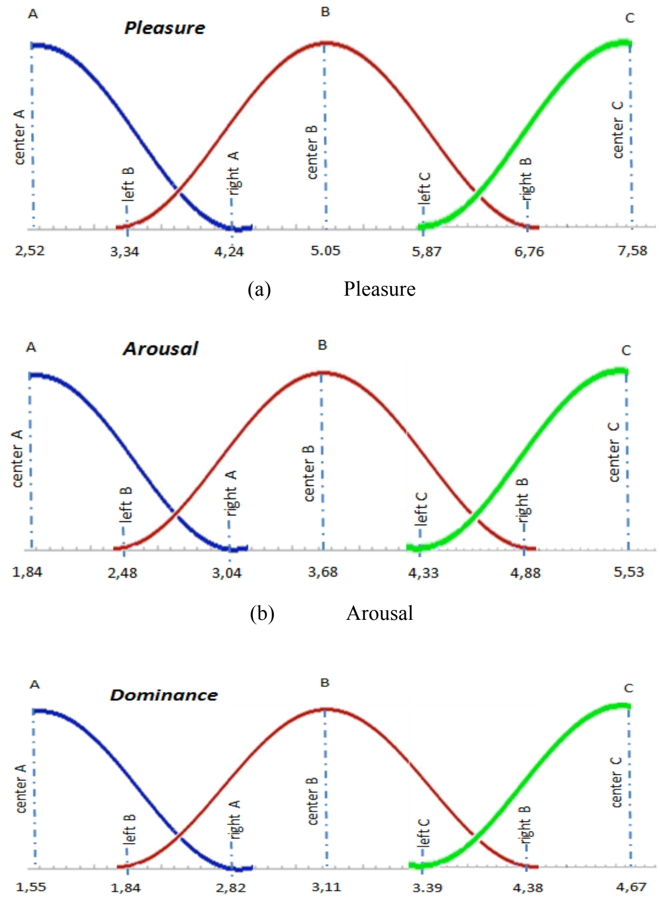
*Variable Name: ***DOMINANCE***	
Mean:	4.67
Standard Deviation (SD):	1.06
Percentage DS :	22.698072805139187
Segment size:	1.5566666666666666
Curves' data of three groups built related to Dominance	
Dominance_Low:	**curveZ** C: 1.5566 LD: 2.8286
Dominance_Medium:	**curvePi** LI: 1.84133 C: 3.113 LD: 4.3853
Dominance_High:	**curveS** LI: 3.3979 C: 4.67

In order to calculate the curves of each group corresponding to each magnitude (Pleasure, Arousal and Dominance), we run our tool three times, one for each dimension.

At each run we gave to the tool the mean of the values for that channel, its standard deviation, a file with the complete group of values for that dimension and a file with the qualitative values for that channel. In this case we used the same qualitative values for the three channels but we configured the tool to establish different qualitative values for each one of the channels.

From these results, we built the curves of the three groups related to each magnitude (Pleasure, Arousal and Dominance).

The graphical representation of the curves obtained for each magnitude are shown in Figs 2(a), 2(b) and 2(c), respectively.



(a) Pleasure

(b) Arousal

(c) Dominance

Figure 2. Resulting Curves for Pleasure (a), Arousal (b) and Dominance (c)

	A	B	C	D	E	F
1	Number	E-Word	S-Word	Pleasure-Fuzzy	Arousal_Fuzzy	Dominance_Fuzzy
2	249	knowledge	conocimiento	Pleasure_High	Arousal_High	Dominance_High
3	172	free	libre	Pleasure_High	Arousal_High	Dominance_High
4	967	safe	seguro	Pleasure_High	Arousal_Medium	Dominance_High
5	734	easy	fácil	Pleasure_High	Arousal_Medium	Dominance_High
6	1014	tidy	ordenado	Pleasure_High	Arousal_Medium	Dominance_High
7	355	respectful	respetuoso	Pleasure_High	Arousal_Medium	Dominance_High
8	62	capable	capaz	Pleasure_High	Arousal_High	Dominance_High
9	226	improve	mejorar	Pleasure_High	Arousal_High	Dominance_High

(a) Fuzzy Values

	A	B	C	J	K	L
1	Number	E-Word	S-Word	Ple-Mn-All	Aro-Mn-All	Dom-Mn-All
2	249	knowledge	conocimiento	7,73	6,29	7,22
3	172	free	libre	8,28	6,38	7,01
4	967	safe	seguro	7,48	4,34	6,90
5	734	easy	fácil	6,92	4,48	6,80
6	1014	tidy	ordenado	6,57	4,19	6,78
7	355	respectful	respetuoso	7,63	4,21	6,76
8	62	capable	capaz	7,52	5,92	6,70

(b) Discrete Values

Figure 3. File contents dicc_fuzzy.txt (a) y (b)

Furthermore, by applying our fuzzification tool to each magnitude results in a text file where each line contains a word from the dictionary, its term in English, its term in Spanish, the values for Pleasure, Arousal and Dominance, and their corresponding numerical values as shown in Fig. 3.

C. *Fuzzy Rules*

The fuzzy rules combine one or more fuzzy entrance groups named precedents or antecedents and they associate them a fuzzy output set named consequences or results. They involve fuzzy sets, fuzzy logic and fuzzy inference. These rules are propositions that allow us to express the available knowledge about the relationship between antecedents and consequents and they make affirmations of the *If-Then* type. The group of various rules constitutes a rules base or knowledge base.

In our model, there has been built 24 rules as a result of combining eight qualitative values obtained for each of the emotional axis of the Plutchick's model as primary, secondary and tertiary dyads as shown in Fig. 4.

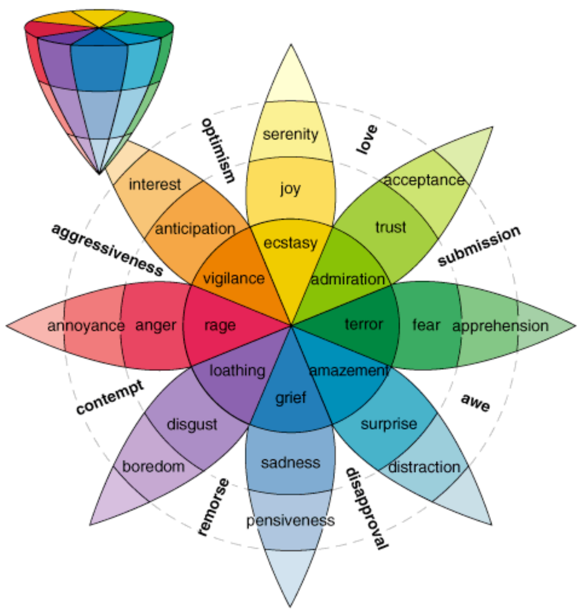


Figure 4. Plutchik's wheel of emotions

Thus, from the basic emotions detected in the text for each word contained in our thesaurus, we obtained by peer evaluation, the associated emotional states to that word. The basic emotions are the antecedents for our rules and the emotional states will be the consequents.

Antecedents
1. Joy
2. Confidence
3. Fear
4. Surprise
5. Sadness
6. Disgust
7. Anger
8. Anticipation

(a) Antecedents

Consequents		
Love	Submission	Flit (Dismay)
Disapproval	Remorse	Contempt
Aggressiveness	Optimism	Fault
Curiosity	Desperation	Envy
Cynicism	Pride	Fatalism
Delight	Sentimentalism	Shame
Outrage	Pessimism	Morbidity
Domination	Anxiety	

(b) Consequents

Rules				
	Antecedent1		Antecedent2	Consequent
If	Joy	&	Trust	Love
If	Confidence	&	Fear	Submission
If	Fear	&	Surprise	Flit (Dismay)
If	Surprise	&	Sadness	Disapproval
If	Sadness	&	Disgust	Remorse
If	Disgust	&	Anger	Contempt
If	Anger	&	Anticipation	Aggressiveness
If	Anticipation	&	Joy	Optimism
If	Joy	&	Fear	Fault
If	Trust	&	Surprise	Curiosity
If	Fear	&	Sadness	Desperation
If	Sadness	&	Anger	Envy
If	Rejection	&	Anticipation	Cynicism
If	Anger	&	Joy	Pride
If	Anticipation	&	Confidence	Fatalism
If	Joy	&	Surprise	Delight
If	Confidence	&	Sadness	Sentimentalism
If	Fear	&	Rejection	Shame
If	Surprise	&	Anger	Outrage
If	Sadness	&	Anticipation	Pessimism
If	Rejection	&	Joy	Morbidity
If	Anger	&	Confidence	Domination
If	Anticipation	&	Fear	Anxiety

(c) Fuzzy Rules

Figure 5. Antecedents (a), Consequents (b) and Fuzzy Rules (c)

If the number of obtained basic emotions for a given word is zero, no single rule is executed. If the number is equal to 1 the basic emotion assigned to that word is returned as its emotional state. Finally, if the resulting number is greater or equal to 2, the rules corresponding to the detected emotions are executed. For each rule two antecedents are evaluated. In case of satisfying it, a unique result is assigned, that result will be a discrete emotional value based in the Plutchick's classification model of emotions.

The dimensional aspect is determined by the color of each petal that varies from soft to intense on intensity according to the emotional experience grade as shown in Fig. 4. The dimensional information is determined from the three fuzzy values corresponding to Pleasure, Arousal and Dominance that allow the teacher to determine the degree of emotional experience from the student or the group of students during their involvements in the virtual classroom.

IV. MODEL TESTING

An experiment was carried out with a class of twenty four fourth-year high school students, attending an activity about computer science, using the Moodle platform. We divided students in eight groups of three members each. The experiment was conducted along five sessions. Questions were proposed in a discussion forum, as shown in Fig. 6. Each member of the group selected one of them and made his/her contribution to the topic. We use students' created-text to train our tool.

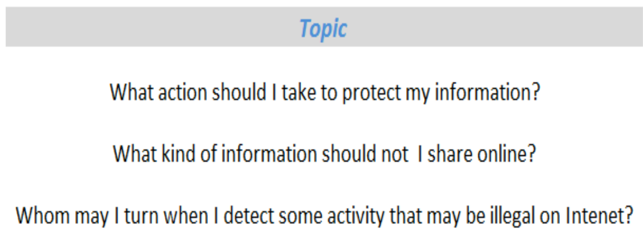


Figure 6. Dissonance cognitive quetions in discussion forum

For the testing our tool, we took the texts produced by the students in various discussion forums. Those texts along the thesaurus built before served as an input for our tool.

The output of the tool consists of a list with the words found in the dictionary and their respective fuzzy values, in addition to the resulting emotional states from the rules application to each one of them.

Once all the text has been processed, the mean of the obtained value for each characteristic is then calculated and the obtained mean values for Pleasure, Arousal and Dominance are fuzzified as shown in Fig. 7.

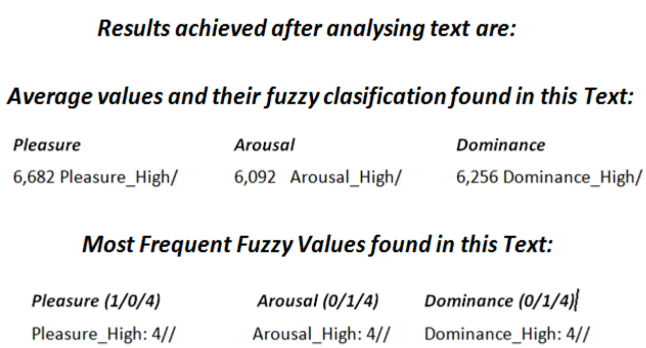
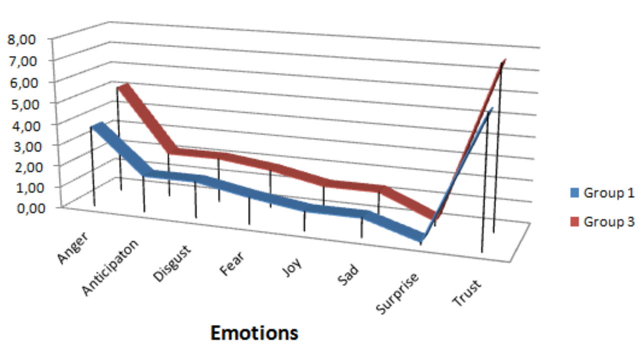
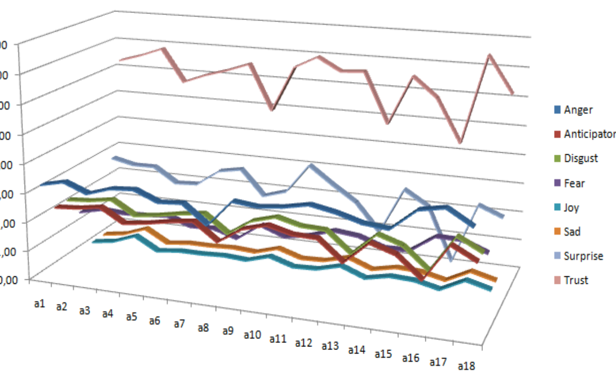


Figure 7. Results after analyzing a text with Fuzzy Model



(a) Groups' emtional states



(b) Students' emtional states

Figure 8. Emotional states of groups (a) and students (b)

The graphical representation of the emotional information associated to each student is shown to the teacher and each student individually. The group's graphical representation of the emotional information of the whole group will be showed to both the group and the teacher, as shown in Figure 8 (a) and 8 (b). Both representations are sent to the activity teacher for his/her knowledge so an appropriate affective feedback can be provided.

V. CONCLUSION AND FUTURE WORK

In this work we have presented a model for Classifying Students' Emotional States in Online Collaborative Work. Our model is encompassed into the Sentiment Analysis Field and aims to be a supporting tool for feedback to teachers interacting with students in a virtual or semi-virtual learning environment.

Our system is based on a fuzzy classification system, which is fed with data from ANEW dictionary, whose words are bound to emotional weights and these, in turn, are used to map Fuzzy sets in our proposal. The proposed fuzzy-based system has been evaluated using real data from collaborative learning courses in an academic context. The results showed the efficiency of the proposed system to classify the emotive states of the involved users.

Our future work is focused on evaluating and improving the tool in order to increase its accuracy. We would like also to test the system with the various rules that we have identified. Those rules can easily be adjusted to different criteria of answers, based on the experience of different experts or different analysis expectations for virtual learning environments in real time.

REFERENCES

[1] Arguedas, M., Daradoumis, T. and Xhafa, F. (2014). Towards an Emotion Labeling Model to Detect Emotions in Educational Discourse. *In proceedings of the 8th International Conference on Complex, Intelligent and Software Intensive Systems (CISIS-2014),* Birmingham, UK, July 2-4, 2014, IEEE Computer Society, Los Alamitos, CA, USA. DOI 10.1109/CISIS.2014.36, ISBN: 978-1-4799-4325-8, pp. 72-78.

[2] Frasson, C. & Chalfoun, P. (2010). Managing Learner's Affective States in Intelligent Tutoring Systems. In Nkambou, R., Mizoguchi,

R. & Bourdeau, J. (Eds.) *Advances in Intelligent Tutoring Systems* (pp. 339–358). Springer-Verlag, Berlin-Heidelberg.

[3] Goetz, T., Pekrun, R., Hall, N., & Haag, L. (2006). Academic emotions from a social cognitive perspective: antecedents and domain specificity of students' affect in the context of Latin instruction. *The British Journal of Educational Psychology*, 76 (Pt 2), 289–308.

[4] Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social Science Information*, 44(4), 693-727.

[5] Tao, Jianhua; Tan,Tieniu (2005). Affective Computing and Intelligent Interaction. *Affective Computing: A Review*. LNCS 3784. Springer. pp. 981– 995. doi:10.1007/11573548.

[6] Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis lectures on human language technologies*, 5(1), 1-167.

[7] Feidakis, M., Daradoumis, T. & Caballé, S. (2013). Building emotion-aware features in Computer Supported Collaborative Learning (CSCL) systems. Alpine Rendez-Vous (ARV) Workshop on Tools and Technologies for Emotion Awareness in *ComputerMediated Collaboration and Learning (ARV 2013).* Villard-de-Lans, Vercors, France. January 28 – February 1, 2013. TELEARC & EATEL associations.

[8] Daradoumis, T., Arguedas, M. and Xhafa, F. (2013). Building Intelligent Emotion Awareness for Improving Collaborative e-Learning. *In proceedings of the 5th IEEE International Conference on Intelligent Networking and Collaborative Systems (INCoS 2013),* September 9-11, 2013, Xi'an, China, IEEE Computer Society, Los Alamitos, CA, USA. DOI: 10.1109/INCoS.2013.49, ISBN: 978-0-7695-4988-0. pp. 281-288.

[9] Ibarrola, B. (2000). L'educació emocional. *Infància*, 116, 5-8.

[10] Isen, A.M. (2000). Positive Affect and Decision Making (ed) *Handbook of Emotions*. Guilford, New York Handbook of Emotions (2nd ed., pp. 417-435). New York: Guilford

[11] Ekman, P. & Friesen, W. V. (1971). Constants across culture in the face and emotion. *Journal of Personality and Social Psychology*,17(2), pp. 124-129.

[12] Ortony, A., Clore, G. & Collins, A. (1988). *The Cognitive Structure of Emotions*. Cambridge: Cambridge University Press.

[13] Pekrun, R. (1992). The Impact of Emotions on Learning and Achievement: Towards a Theory of Cognitive/Motivational Mediators. *Applied Psychology: An International Review*, 41(4), pp. 359-376.

[14] Russell, J. A. (1983). Pancultural aspects of human conceptual organization of emotion. *Journal of Personality and Social Psychology*, 45, 1281-1288.

[15] Plutchik, R. (2001). The nature of emotions. *American Scientist*, 89,34-350.

[16] Kort, B. & Reilly, R. (2002). Analytical Models of Emotions, Learning and Relationships: Towards an affectsensitive cognitive machine. *Proceedings of the International Conference on Virtual Worlds and Simulation (VWSim 2002)*, San Antonio, Texas

[17] Scherer, K.R., Shuman, V., Fontaine, J.R.J, & Soriano, C. (2013). The GRID meets the Wheel: Assessing emotional feeling via selfreport. In Johnny R.J. Fontaine, Klaus R. Scherer & C. Soriano (Eds.), *Components of Emotional Meaning: A sourcebook* (pp. 281-298). Oxford: Oxford University Press

[18] Andreevskaia, A. & Bergler, S. "Mining WordNet for a fuzzy sentiment: Sentiment tag extraction from WordNet glosses," in *Proceedings of the European Chapter of the Association for Computational Linguistics (EACL)*, 2006.

[19] Kuncheva, Ludmila. *Fuzzy classifier design*. Vol. 49. Springer Science & Business Media, 2000.

[20] Redondo, J., Fraga, I., Padrón, I., & Comesaña, M. (2007). The Spanish adaptation of ANEW (affective norms for English words). *Behavior research methods*, 39(3), 600-605.

[21] Wundt, W. M. (1896). *Compendio de psicología*. La España Moderna.

[22] Osgood, C. E., Suci, G. J., & Tannenbaum, P. H.1957: *The Measurement of Meaning. Urbana*, IL: University of Illinois Press.

[23] Bradley, M. M., & Lang, P. J. (1999). Affective norms for English words (ANEW): Instruction manual and affective ratings (pp. 1-45). *Technical report C-1, the center for research in psychophysiology*, University of Florida.

[24] Whissell, C. (2009). Using the revised dictionary of affect in language to quantify the emotional undertones of samples of natural language 1, 2.*Psychological reports*, 105(2), 509-521.

[25] Mohammad, S. M., & Turney, P. D. (2013). NRC Emotion Lexicon. *NRC Technical Report*.

[26] Baccianella, S., Esuli, A., & Sebastiani, F. (2010, May). SentiWordNet 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining. *InLREC* (Vol. 10, pp. 2200-2204).

[27] Mehrabian, A., & O'Reilly, E. (1980). Analysis of personality measures in terms of basic dimensions of temperament. Journal of Personality and Social Psychology, 38(3), 492..

[28] Becker, C., Kopp, S., & Wachsmuth, I. (2007). Why emotions should be integrated into conversational agents. *Conversational informatics: an engineering approach*, 49-68.

[29] Mehrabian, A. (1972). Nonverbal communication. *Transaction Publishers*.