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Architecture for Emotional Pedagogical Agent

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Abstract: **Education and pedagogy are very important issues in human life. So, computer scientists have tried to model educational environment to computer world for several decades. But, there are a few researches about role of emotion in tutoring systems. In this article, architecture for emotional pedagogical agent is presented. The emotional pedagogical agent models emotional states of a student and tries to use the student's emotions as a guide and evaluator for teaching.**

We use neuro-fuzzy networks to model emotional state of the student. The model is applied by emotion aspect of pedagogical agent to be more compatible and useful for the student. We hope that we can get through realization of the far away aim.

Index Terms**: Pedagogical agent, emotional agent, neurofuzzy network, reinforcement learning.**

1. Introduction

Today, several decades after the birth of the Internet, in many branches of science, scientists try to omit distances for two reasons. First, to decrease cost of gathering in one place. Second, to compensate for limitation or lack of the expert. So we need to capture the knowledge of the experienced teachers and transfer it to the software systems.

Tutoring system has an old history, but the first tutoring systems work as a static media. After awhile Intelligent Tutoring Systems (ITS) were designed. ITS is an intelligent system which adopts with students and teaches on the basis of characteristics and capabilities of them.

In other way, for the past several years, the emotional agent has been studied. El-Nasr investigated the use of uncertainty of emotions in the decision making process of mobile robot [3].In Gadanho's work a non-symbolic emotion model was developed that takes the form of a recurrent artificial neural network where emotions both depend on and influence the perception of the state of the world [4].an architecture of mind is presented with the ability to display adaptive emotional states of varying types and intensities by McCauley [8]. Ventura proposed a model for an agent whose functioning is based on emotion [15].

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With junction of ITS and emotional agent, emotion was used in the tutoring system. So pedagogical agents were designed that use emotion. But, in the most research, emotion is used in dialogue and interface part. Elliott explored how affective computing can be incorporated into pedagogical agent to improve students' learning experience [2]. Lester exploited the visual channel to more effectively communicate with learners, too [7]. Person attempted to incorporate human-like conversational behaviors into an animated pedagogical agent that simulates the dialog moves of human tutors [12]. Rickel developed computer tutors that collaborate with students on tasks by using computational models of human dialogue in simulated environments [14]. Unfortunately, less effort has been done in decision maker role of emotion in training and education. For instance, Gratch in his paper described a model of emotional reasoning for an automated tutor by applying explicit planning model [5]. Vicente focused on the detecting the student's motivational state [16].

In this work the pedagogical agent is designed on the basis of the capabilities of the emotional agent. We proposed an architecture who uses emotion in both of making dialogue with student and also making decision about continue of training process. Furthermore, this architecture has the ability of real time decision making and also it can increase its knowledge about its built-in fuzzy rules. We implemented emotional and motivational states of students in a pedagogical environment. With this research, we hope that we can get through realization of the far away aim.

In the past, there was a distinct border between emotions and rational thoughts of human beings. So, human was trying to omit their emotions to make rational decisions. In fact, we have been conditioned to think that emotions were not a part of human intelligence, but rather hinder humans' thoughts. This idea has been initiated by ancient philosophers such as Plato. Moreover, Descartes reinforced this idea by his famous quote "I think therefore I am."

But today these concepts have been changed. Rational behavior is the behavior that avoids non-pleasurable states and/or pursues pleasurable states [1]. So, emotions became necessary and an important factor for intelligent thoughts and acts [6] [13]. Minsky concluded that, "the question is not whether intelligent machines can have any emotions, but whether machines can be intelligent without any emotions "[9].

The nature of emotion has been debated in psychology for the past one hundred years. For example, Picard [13] reminds us that nearly a hundred definitions of emotions have been categorized. A definition of the term emotion is given by Parkinson [11] “An emotion is a relatively short-term, evaluative state focused on a particular intentional object (a person, an event, or a state of affairs). Good examples are anger, fear, love, and hate”.

There are also lots of definitions for motivation. Psychologists (especially cognitivists and behaviorists) don’t agree with unique definition. But generally motivational states are feelings that might drive the brain to interrupt its normal activity to concentrate on a higher need. Weiner [17] writes: “Motivation is the study of the determinants of thought and action; it addresses why behavior is initiated, persists, and stops, as well as what choices are made”.

After proving that emotions are crucial in all aspects of human life by psychologists, emotional agents have been considered by computer scientists. Emotional agents try to capture human emotions and motivations, and use the capabilities of these emotions [15]. By studying these two branches, we suggest architecture for pedagogical agent that acts based on emotions.

2. Suggested Architecture

Fig. 1 outlines an Intelligent Tutoring System. It generally has three modules: domain module, student module and tutorial module. The domain module contains the knowledge about the domain. It must contain different alternatives for lessons and exercises. The student module contains information about a student. In fact, in this module a model of student is saved. The tutorial module contains knowledge about tutoring. Every decision is taken in tutorial module.

But our suggested architecture proposes a pedagogical agent as a substitute for ITS. Agents have several characteristics such as being autonomous, cooperative, active, reactive and etc. Most of these properties are necessary for a tutoring system, so a pedagogical agent can play the role of a real teacher in a more believable way.

The pedagogical agent still contains a domain module, a student module and a tutorial module. But, these modules have been changed. For instance, the student module of the pedagogical agent in the suggested architecture saves an emotional agent for every student. We model the emotional state and actions of students; because the pedagogical agent acts and makes decisions on the basis of this impression of students. In fact, inside the pedagogical agent, there is one agent for every interacted student. In the next parts, we describe these subjects in more detail.

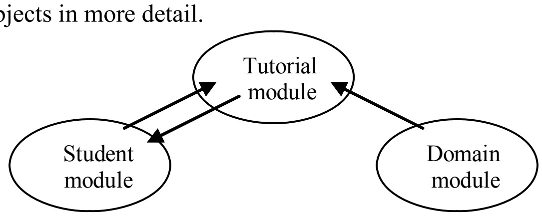

Fig. 1: Modules of Intelligent Tutoring System

In Fig. 2, a general architecture for the emotional pedagogical agent is presented. In this picture student module and tutorial module have been determined.

Students (smiley face) can interact with pedagogical agent. Pedagogical agent is composed of student module, tutorial module and domain module. In student module, On the basis of general fuzzy rules and self report unit, student agent for each interacted student is developed. The student agent stores emotions and motivations of student. Emotions and motivations of student change on effect of learning process; therefore, they are stored and change with neural networks (the box with this title "Neurofuzzy system for diagnosis next emotional state").

In pedagogical agent, all of decisions about teaching process are taken. It contains three parts. In *analytical deciding unit*, pedagogical agent select next lesson or exercise on the basis of student agent emotional state. Pedagogical agent makes real time decision in *perceptual deciding unit.* In *event memory unit*, pedagogical agent saves states changes and environmental conditions then it can find more rules by applying data mining algorithm on this memory.

Now, we present the detailed explanation of the architecture. As you see, the domain module is not shown in Fig. 2, because it is not considered a technical part. It contains lessons and topics. The domain module must contain different lessons and exercises about special topics. The tutorial module selects desired lessons or exercises of the domain module for a student on the basis of the student module.

1.1. Student Module

In this module, we model the student's emotional agent. So we must consider her/his emotional and motivational characteristics and also her/his actions. Scientists who model emotion usually work on specific emotions, such as anger, happiness, sadness, joy, fear, etc. But, in educational environments, there are specific emotions which have a more important role in the learning process. In the real world, we must save a lot of properties for modeling a student but since the task is very hard, we try to minimize properties that we must save. We save a static motivational model (characteristics) and dynamic motivational model (emotions) [16]. The static motivational model contains:

Control, Fantasy, Independence and Challenge. Also, the dynamic motivational model contains: *Confidence, Effort, Satisfaction, Cognitive Interest and Sensory Interest*. The motivational model is presented in Fig. 3.

Control refers to the degree of control that the student likes to have over the learning situation. *Fantasy* refers to the degree that the student appreciates environments that evoke mental images of physical or social situations not actually present. *Independence* refers to the degree that the student prefers to work independently, without asking others for help. *Challenge* refers to the degree that the student enjoys having challenging situations during the instruction.

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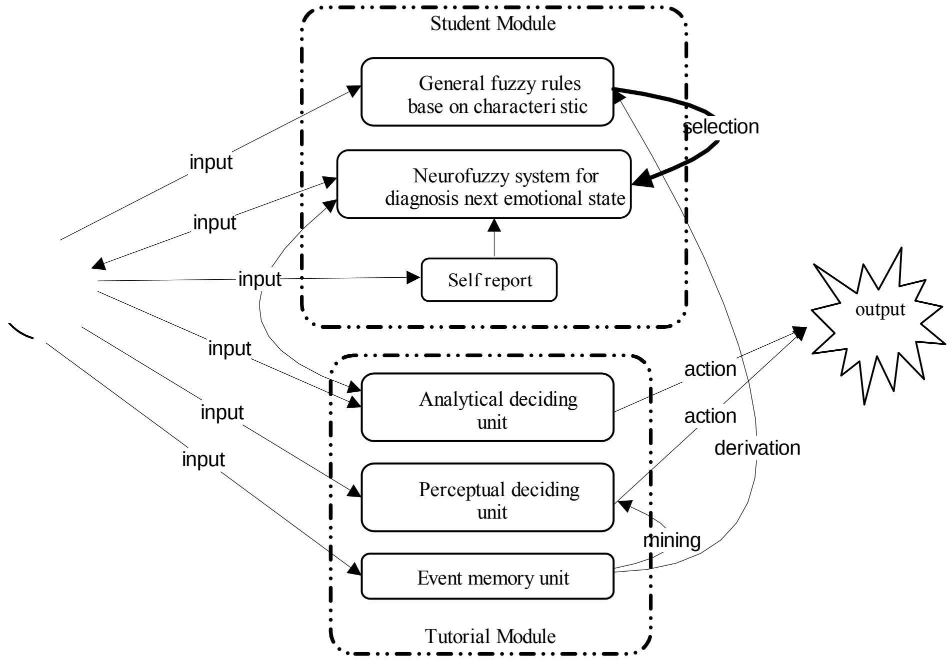

Fig. 2: Suggested Architecture for Emotional Pedagogical Agent

Confidence refers to the student's belief in being able to perform the task at hand correctly. *Effort* refers to the degree that the student is exerting himself in order to perform the learning activities. *Satisfaction* refers to the overall feeling of goal accomplishment. *Cognitive Interest* refers to curiosity aroused through the cognitive or epistemic characteristics of the task. *Sensory Interest* refers to the amount of curiosity aroused through the interface presentation [16].

The motivational model components are fuzzy variables. Each component has five fuzzy sets (*very low, low, average, high, and very high*). The Gaussian membership functions are used for each component as shown in Fig. 4.

$\mu_{\text{Very Low}}(x) = \exp\{-((x+10)/2.5)^2\}$
$\mu_{\text{Low}}(x) = \exp\{-((x+5)/2.5)^2\}$
$\mu_{\text{Average}}(x) = \exp\{-((x)/2.5)^2\}$
$\mu_{\text{High}}(x) = \exp\{-((x-5)/2.5)^2\}$
$\mu_{\text{Very High}}(x) = \exp\{-((x-10)/2.5)^2\}$

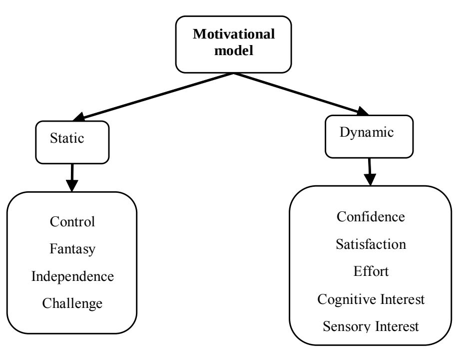

Fig. 3: Motivational Model

But how can we find or estimate the student's emotional state? In the next section, we focus on this problem

2.1.1. Emotion Detection

The important problem is how we detect the student's emotional state. For example, how can we confirm that confidence is high? For solving this problem we have four solutions.

1- Self report
2- Motivation diagnosis by rules
3- Speech analysis
4- Image processing

In the third and fourth solutions, emotions are detected from the student's speech and face. In this paper, these topics haven't been included.

2.1.1.1. Self Report

In this solution, we ask our questions about the student's emotion directly from the student. The student must respond honestly. This solution although very easy, has two disadvantages:

1- Repeating these questions is boring for a student.
2- The student may not respond honestly.

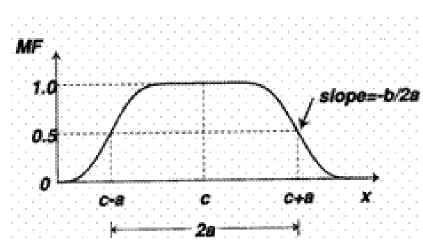

Fig. 4: Gaussian Membership Function

Even though this way is good for static motivation, but this solution isn't enough for dynamic emotion detection. However, we can use this solution with other solutions. We can ask these questions in a specified period, therefore it won't be boring for a student. For example, we ask a question to focus on the confidence as follows: *how correctly do you believe you can perform the task at* hand (very high, high, average, low, and very low)?

2.1.1.2. Motivation Diagnosis by Rules

At First, the pedagogical agent makes an imagination of the emotional state of the student agent. But it is far from real state of student. So, the pedagogical agent tries to learn more about the student's emotions on the basis of his actions. Furthermore, his emotions are dynamic and change after each interaction. Because of these reasons the pedagogical agent needs to use the neural network to model the emotional state of the student agent.

In this way the dynamic motivations (emotions) are modified by neuro-fuzzy networks. Neuro-fuzzy networks are designed on the basis of the specified rules. They start with initial fuzzy evaluation and then they can learn. So, they are more clear and more speedy than neural-networks. Because of these reasons, we capture the knowledge of the expert and express them with fuzzy rules. Then, the neuro-fuzzy networks can be initialized by fuzzy rules.

In this case, we have some fuzzy rules that predict motivation from previous motivational states, performance and teaching materials. These rules are designed by Vicente [16]. You see some of these rules in Tables 1 in the Appendix.

With the above rules, we designed appropriate neuro-fuzzy networks. We designed nine neuro-fuzzy networks for increase satisfaction, decrease satisfaction, increase confidence, decrease confidence, increase effort, decrease effort, increase cognitive interest, decrease cognitive interest, increase and decrease sensory interest.

One of neuro-fuzzy networks is presented in Fig. 5.You have seen it's rules in Table 1. They are based on static and dynamic motivations, performance, and teaching materials. Static motivations are constants; so it isn't necessary to bring them into neuro-fuzzy networks. Furthermore, some rows in rule's table are dependent on static motivations. For example, in Table 1 row 9, we have *if control is high and … then satisfaction is high*. It is clear that if control isn't high initially, it isn't necessary to check other factors until the process is finished. So, we can design smaller neuro-fuzzy networks, when static motivation doesn't satisfy specified conditions. For example, if both control and challenge are not high, we can build a neuro-fuzzy network as Fig. 6.

These neuro-fuzzy networks are initialized by the fuzzy rules; therefore initial weights in neuro-fuzzy networks are quantified. The edges which exit from a node inherit equal part as its weight. For instance, if two edges exit from a node, both of initial weight will be 0.5, and then neuro-fuzzy networks improve themselves.

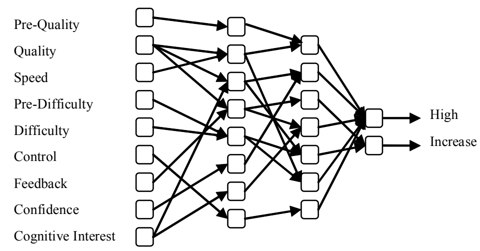

Fig. 5: Increase Satisfaction Neuro-fuzzy Network

In this environment, we don't have any exact or correct response for the neuro-fuzzy networks; therefore, we couldn't use a supervised learning algorithm on the neuro-fuzzy networks; thus, we decided to use reinforcement learning for teaching our networks. With increase or decrease signal, the weights of edges will be changed. So our learning is done by an emotional evaluator, too.

If increase or decrease signal becomes active in a pass, weights will modify on the basis of Residual Gradient Algorithm.

$$\Delta w_t = \alpha\left[r(x_t) + \gamma V(x_{t+1}, w_t) - V(x_t, w_t)\right]$$
$$\left[\gamma \partial V(x_{t+1}, w_t) / \partial w_t - \partial V(x_t, w_t) / \partial w_t\right]$$

In this context, α is learning rate, γ is a discount factor in the range [0, 1], V (x_t,w_t): actual output of the network and $\partial V(x_t,w_t)$)/ ∂w_t is the gradient of the output of the network with respect to the w_t. But $r(x_t)$ is the reinforcement received and equals to: value (Inc or Dec signal)/15; therefore: $-1 \leq r(x_t) \leq 1$.

Therefore, in the student module, a neuro-fuzzy network for emotion is initialized by the self report unit, and then it is modified with rules that are built-in.

2.2. Tutorial Module

In this module, the pedagogical agent decides about everything. Furthermore she/he speaks with a student. The tutorial module makes decisions on the basis of the emotional state of the student agent. In fact, it teaches the student by considering the student's emotion. So, the student will have more motivation and interest to learn new subjects. As you saw in Fig. 2, the Tutorial module has three units. We explain each unit as follows:

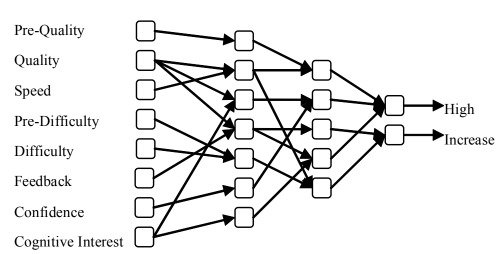

Fig. 6: Increase Satisfaction Neuro-fuzzy Network (with omitting rows 6, 9)

2.2.1. Analytical Deciding Unit

In this unit, the pedagogical agent decides about continuation of lessons and exercises and interacts with a student. This task is decided with rules. The rules aren't fuzzy, because responses are discrete. First, the pedagogical agent decides the difficulty level of next lesson or exercise. This decision is taken based on student's emotions (*Confidence, Effort, Satisfaction, And Cognitive Interest*). These rules can be determined by a complete pedagogical research and on the basis of theories and experiences of pedagogical psychologist researchers.

When the difficulty level of the lesson or exercise is specified, the pedagogical agent selects an appropriate lesson or exercise from the domain module according to the rules. For example, if (confidence<average) and (effort>=average) then difficulty will become lower. Because the student spend enough effort but her/his confidence is low, to increase her/his confidence we give her/him an easier exercise. But if (confidence>=average) and (effort<average) and (cognitive interest <average) then difficulty will become much higher. Because the student does not spend enough effort and she/he is not cognitively interested but she/he has high confidence. So, the subject or exercise is probably too easy for the student and we must give her or him much more difficult exercise.

Also, for speaking with a student, the pedagogical agent uses other rules. These rules can be designed on the basis of the student's emotions (*Confidence, Effort, Satisfaction, Cognitive Interest, And Sensory Interest*) and the quality of the student's performance on the current and previous section. For example, if (confidence<average) and (effort>=average) and (quality>=average), pedagogical agent will say encouragement sentence to increase her/his confidence. Or if (confidence>=average) and (effort<average) and (cognitive interest <average) and (quality>=average) pedagogical agent will invite her/his to challenge.

2.2.2. Perceptual Deciding Unit

In this unit, the pedagogical agent decides about tasks that don't need thinking and consider the emotional state of a student. So it decides real time. For example, when a cognitive interest of student become less than a minimum threshold. We defined these situations and appropriate reactions of the pedagogical agent in a database. So the pedagogical agent can act on the basis of it. Each time a specified event occurs, the pedagogical agent acts according to that reaction.

2.2.3. Event Memory Unit

Our pedagogical agent can use her/him experience and can modify herself/himself. When the self report unit or analytical deciding unit causes changes in emotional state, the pedagogical agent saves changes of the motivational model, teaching material and performance in the event memory. In specified times, the pedagogical agent reviews event memory and tries to find relations. If she/he finds that repeated states cause similar emotional state change, she/he will build a new relation and adds it to general fuzzy rules.

3. Implementation

We have implemented the suggested architecture for a pedagogical agent. To do this work, we used an animated character. The animated character was named Merlin. He was implemented by Microsoft. Merlin is programmable. He has a set of gestures and actions. So he can show some emotions. We used him only for showing some actions and feeling of a teacher. We can program him by Microsoft language. So, we chose Visual C# and SQL SERVER 2000 as a DBMS. We implemented the teacher agent and the student agent as two different threads that can interact together. In the student thread, neuro-fuzzy networks are created and modified. So, we create the emotional model for the student in the student module .In the teacher thread, all decisions are made, it implements the tutorial module. Neuro-fuzzy networks are created on the basis of initial static and dynamic motivations. These motivations are asked by two forms in self report units. You see one of the forms as shown in Fig. 7.

Also, neuro-fuzzy networks are modified by the student's interactions. Some forms were designed for lessons and exercises. The student interacts with a teacher by these forms and the teacher selects teaching forms and exercise forms on the basis of the student’s emotional state.

4. Conclusions

In this article, architecture for an emotional pedagogical agent is suggested. The pedagogical agent models emotional state of a student and tries to adopt her/his teaching accordingly. The pedagogical agent models with neuro-fuzzy networks and uses specified rules for decisions about continuation of teaching. The pedagogical agent can improve herself/himself. She/he can use memory and data mining algorithms for this purpose.

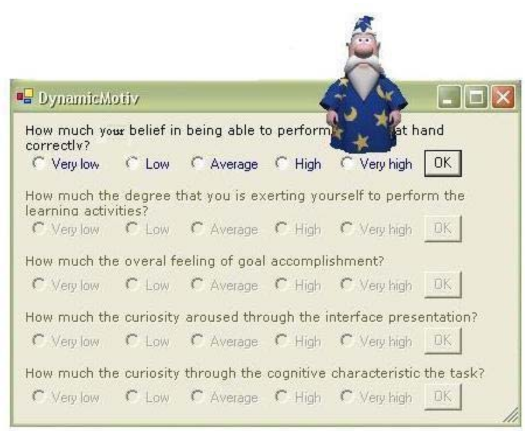

Fig. 7: Questions of the Dynamic Motivation

APPENDIX

Table1. Increase Satisfaction Diagnosis Rules

	PERFORMANCE			TEACHING MATERIALS				MOTIVATION MODEL				MOT. TRAITS		
Rule	pre(Quality)	Quality	Speed	pre(Difficulty)	Difficulty	Control	Feedback	Satisfaction	Confidence	Effort	Cognitive interest	Control	Challenge	Output
IS1		High							High		High			High
IS2	Low	High	Fast											High
IS3		High					Enc							Inc
IS4		High					Enc				High			High
IS5											High			High
IS6		High		X	>X					High			High	High
IS7		High	Fast	X	>X									Inc
IS8				X	<X			Low	Low					Inc
IS9						High						High		High

REFERENCES

[1] A. Damasio, "Emotion , reason and human brain", Picador, London, 1994.

[2] C. Elliott, J. Rickel, and J. C. Lester, "Lifelike Pedagogical Agents and Affective Computing: An Exploratory Synthesis", Journal of Artificial Intelligence Today , 1999, pp. 195-211.

[3] M. S. El-Nasr, and M. Sleubic, "A Fuzzy Emotional Agent for Decision-Making in Mobile Robot", Proceedings of the 1998 Int. Conf. On Fuzzy Systems (FUZZ-IEEE'98), May 1998, pp. 135-140.

[4] S. Gadanho, and J. Hallam, "Robot learning driven by emotions", Adaptive Behavior, 9(1), 2001.

[5] J. Gratch,, "Emile: Marshalling passions in Training and Education", in 4th International conference on Autonomous Agent, June 2000.

[6] J. LeDoux, *The Emotional Brain*, Simon & Schuster, 1996 .

[7] J. Lester, S. Towns, and P. FitzGerald, "Achieving Affective Impact: Visual Emotive Communication in Lifelike Pedagogical Agents". in International Journal of Artificial Intelligence in Education.Vol .10 , 1999 pp. 278-291.

[8] L. McCauley, and S. Franklin, "An Architecture for Emotion", Available: http://www.msci.memphis.edu/~cmattie/ArchitectureForEmotion.pdf, 2000.

[9] M. Minsky, *The Society of Mind*, Touchstone,1988.

[10] J. ed. Odell, "Agent Technolog"y, OMG, green paper produced by the OMG Agent Working Group, 2000.

[11] B. Parkinson, *Emotion*, chapter 1. In Parkinson and Colman, 1995.

[12] N. K. Person, C. Craig , P. Price, X. Hu, B. Gholson, A. C. Greasser, and the Tutoring Research Group "Incorporating human-like conversational behaviors into AutoTutor". In the Agents 2000 Proceedings of the Workshop on Achieving Human-like Behavior in the Interactive Animated Agents,Barcelona, Catalonia, Spain: ACM Press,2000, pp. 85-92.

[13] R. Picard, Affective computing , Technical Report 321 , M.I.T , Media Laboratory, 1997 .

[14] J. Rickel, N. Lesh, C. Rich, C.L. Sidner, and A. Gertner, "Building a Bridge between Intelligent Tutoring and Collaborative Dialogue Systems". In Proceedings of Tenth International Conference on AI in Education, May 2001, pp. 592-594.

[15] R. Ventura, *Emotional Agent* , M.Sc thesis , lisboa, 2001.

[16] A. D. Vicente, "Towards tutoring systems that detect students' motivation: an investigation". Ph.D. thesis, School of Informatics, University of Edinburgh, UK, 2003.

[17] B. Weiner, *Human Motivation: Metaphors, Theories, and Research*. Sage Publications Inc., Newbury Park, London, 1992.