Emotion Modeling for Simulation of Affective Student-Tutor Interaction: Personality Matching

Sintija Petrovica and Mara Pudane

Abstract**—**Ever since the field of intelligent tutoring began to develop, one of its main purposes has been to create a personalized learning environment to imitate one-to-one interaction between a student and a human-tutor. Although there have been a significant progress towards achieving this goal both from methodological and affective point of view, current systems are not truly adaptive to a student. It is believed that one of reasons for that is the lack of system's personalization itself, and particularly through its representation to user - virtual tutor. To close this gap, it is proposed to generate tutor's personality based on user's personality. The paper introduces steps of personality modeling for such system as well as tutor's personality generation. This enables creating an attractive virtual tutor that serves for a common goal of the research - truly adaptive intelligent tutoring system.

Keywords**—**Agents, emotion modeling, intelligent tutoring systems, personality.

I. Introduction

ALMOST half a century intelligent tutoring systems (ITSs) have been developed to imitate the learning process of a student and a tutor interaction in a one-to-one tutoring situation. The main goal of ITSs is to provide adapted tutoring in a certain problem domain for a particular student, considering his/her knowledge and individuality during teaching process. However, recent study in psychology, neuroscience, pedagogy, and cognitive science has shown that emotions play a key role in the learning process, decision making, motivation, and understanding [1].

As a result, over the last decade researchers inspired by the close relationship between emotions and learning have been working on the integration of an affective component into human-computer interaction. This has led to creation of a new generation of ITSs – affective tutoring systems (ATSs) that are able not only to support the learning process but also to recognize student's emotions, respond to them by adapting tutoring process, and show emotions of the tutoring system itself using animated pedagogical agents. However, expressions for same emotions may differ between various students and regarding this issue a personality can give cues to patterns of emotion expression [2] because personality represents those characteristics of the person that are related to persistent ways of feeling, thinking, and behaving allowing to predict and explain these actions [3].

Students have different personalities, characteristics, needs, knowledge background, preferences, learning styles, emotions and all these factors can influence learning process and knowledge acquisition. Also tutors have their own personalities, ways of teaching, etc. that can affect an efficiency of teaching and learning process as well. But how to know, which will be the most effective tutor's personality and a way of teaching for particular student to positively influence student's emotional state, motivation, interest, behavior, and learning progress? Although this question is complex and interdisciplinary, we propose that well-developed affective tutoring system might help pushing the state of the art in related fields such as pedagogy and psychology as well. The final version of such a system would allow the simulation of human-tutors' and students' interaction to test different tutor's personalities and their teaching methods. This goal includes complex multidisciplinary research. The use of a multi-agent system (involving tutor agents and student agents) as a natural metaphor, as well as the student's personality modeling and matching with initial tutor's personality and their emotion modeling are introduced and explained in the paper.

II. Affective Agent-Based Tutoring System

In this section, main challenges regarding tutoring adaptation to students' emotions are discussed. The section gives brief theoretical background into affective intelligent tutoring systems and their architecture, as well as explores suitability of multi-agent approach for the development of ITS's components. A conceptual architecture of agent-based ATS for the interaction simulation between human-tutors and students is designed.

A. Intelligent Tutoring Systems and Agents

Intelligent tutoring systems are a generation of computer systems which aim to support and improve teaching and learning process in certain knowledge domain. ITSs simulate a human-tutor and provide benefits of one-on-one tutoring. ITSs

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are specific type of intelligent systems that exploits principles and methods of artificial intelligence (AI) to provide individualized teaching process. Such systems allow providing more natural learning process by adapting a learning environment (content, feedback, navigation, etc.) to the characteristics of a particular student. Adaptation is possible because of integrated knowledge into traditional architecture which includes [4]:

- a student diagnosis module collecting and processing information about the student (his/her learning progress, problem solving behavior, psychological characteristics, etc.) and a student model that stores this knowledge about a student;
- a pedagogical module responsible for implementation of the teaching process and a pedagogical model storing pedagogical knowledge, e.g. teaching strategies, methods, etc.;
- a problem domain module able to generate and solve problems in the problem domain and a domain model storing knowledge what must be taught to the student;
- an interface module managing interaction among the system and the student through input/output devices.

The contemporary approach in the AI field is related to an agent paradigm [5]. Many systems for educational purposes have adopted agent approach to explore the interaction and dynamic changes related to learning and teaching process. Agents are able to provide adaptive behavior, react to environmental changes, plan their actions, predict, reason, learn, and operate in dynamic environments. The common practice is to combine several agents in a single system, thus forming a multi-agent system where agents interact and cooperate together to reach common goals. Taking into account agent capabilities, multi-agent architecture is suitable for the ITS development due to following reasons: [4]:

- ITS should plan the learning process and communication with the student;
- ITS must perform multiple, different tasks, including student's monitoring and reacting to his/her behavior, student's knowledge assessment, choosing of learning material and tasks, provision of feedback and help, adaptation of teaching strategies, etc.;
- system's behavior and operations are changing with each student's action, therefore, it must demonstrate reactive behavior;
- ITS needs to acquire information about the student and take into account his/her cognitive, psychological, and affective characteristics in order to adapt the learning/teaching process;
- ITS architecture consists of several components with independent functions but all components must interact with each other to achieve the common goal – adapted tutoring for an individual student.

An interaction between agents is a defining characteristic to reach previously mentioned ITS's goal. One of the ways to initiate and maintain interaction among agents is their participation in communication that enables agents to base their decisions on more complete knowledge of overall situation. Effective interaction and communication among agents requires three fundamental and distinct components [6]: a common language; a common understanding of the knowledge exchanged; the ability to exchange whatever is included in the first two components. An explicit representation of knowledge is an essential task to ensure ITS functionality and usage of domain knowledge, knowledge about the student, and pedagogical knowledge related to teaching strategies and methods for domain knowledge transfer.

B. Intelligent Tutoring Systems and Emotions

As mentioned in previous section, the learning with ITS is very similar to the process when a student and a tutor interact in a one-to-one situation, which, according to Benjamin Bloom [7], is an ideal condition for learning. Therefore, an effective intelligent tutoring should simulate what good human-tutors do when implementing individualized instruction. Despite the considered fact that developed ITSs are capable to adapt teaching process similar as human-tutors do, there is still a gap between perfect adaptation skills and current developments. The main reason for this gap is considered the ITS's lack of an emotional intelligence [8]. It is important to add that emotion understanding can be confusing task even for humans because each emotional state has its own reasons and might be expressed in various ways and influence subsequent behavior differently. Though, tutors can evaluate emotional states of a student with a rather high reliability on the basis of facial expressions, body language, and speech. Consequently, experienced human-tutors can adapt the teaching process taking into account the student's knowledge level, emotional state, and behavior during learning.

Previous studies have shown that emotions can influence various aspects of human behavior and cognitive processes, such as attention, long-term memorizing, decision making, understanding, remembering, analyzing, reasoning, and application of knowledge in task solving [9, 10]. Emotional states such as confusion, curiosity, interest, flow, joy, boredom, frustration, and surprise have become particularly relevant in learning and can influence student's problem solving abilities and even affect willingness to engage in the learning process, as well as they can increase or decrease motivation to learn [11]. As a result, affective (or emotionally intelligent) tutoring systems started to evolve with ability to recognize student's emotions and to respond to them by adapting tutoring process and showing emotions of the tutoring system itself [12].

ATS functionality requires inclusion of not only already previously listed knowledge regarding students, problem domain, and pedagogy but also a common representation and understanding of emotions. In terms of agent-based ITSs, an explicit emotion representation enables agents to imitate possible student's reactions during the learning process and to express them to pedagogical agents (tutors). Pedagogical agents, in turn, can recognize reason and act on emotions by changing tutoring situation accordingly, adapting pedagogical activities, as well as expressing its own emotions.

C. Adaptation Issues in Affective Tutoring Systems

Currently, many ITSs are rebuilt to include capabilities for the emotion recognition, emotion modeling and tutoring process adaptation [13, 14], however, greater attention has been paid to detection and classification of student's emotions. Thus, a problem how to adapt tutoring to a student's emotional state still remains unsolved [15, 16].

Providing students with cognitive and affective support is generally recognized as an important condition for successful learning. Nevertheless, more research is needed that would allow to explain how both types of support may be included in tutoring strategies and how to implement them in ITSs as part of the pedagogical module. Traditionally, the pedagogical module is ITS component that imitates the human-tutor and determines appropriate tutoring strategies, adapts the tutoring process (chooses the next topic and its presentation type, tasks to solve and their difficulty, type of assistance and feedback, etc.) depending on the curriculum, student's cognitive needs, and abilities. Moreover, this module plans and manages interaction with the student [17].

It should be noted that there is no "one-size-fits-all" strategy in pedagogy because students have different personalities, characteristics, needs, knowledge background, preferences, learning style, etc., as well as emotions that can influence his/hers learning [18]. Therefore every student should have different tutoring approach that would allow ensuring the knowledge acquisition and maintenance of the optimal emotional state for the student. Many ITSs make decisions that are inappropriate for the student in terms of their profile, personality and emotional characteristics (due to inconsistencies in the presentation style, an inadequate level of content or strategy to address tutoring situation) thus negatively influencing student's performance during the learning [19].

D. Conceptual Architecture of Agent-Based Affective Tutoring System

Overall, multi-agent system approach offers several benefits which are useful in the development of long term adaptive systems. Affective tutoring system can be considered as a long term adaptive system because it should follow students during several courses rather than few tasks within one learning session. In this case, a system has to model student in a believable manner, as well as store the previous knowledge structure and behavior of the student. First of all, multi-agent approach allows building a dynamic and easily changeable system (several students and tutors can be added). Secondly, students' agents are autonomous units which are able to "experience" emotions and exhibit student-like behavior. This property enables student simulation before content adaptation for a real student. Finally, in a system with clearly defined roles (e.g. several students and corresponding tutors) the agent mechanisms allow the design of the system to be more intuitive [20].

To support both emotional and cognitive aspects, the architecture of multi-agent based affective tutoring system is proposed (see Fig.1.). Adaptation of the tutoring process is planned through the creation of personalized emotional pedagogical agent for the particular student (student agent) based on student's characteristics. Each student learns better with particular type of tutors because they also have their own personality, the way of teaching, appearance, etc., that can affect an efficiency of teaching and learning process [21].

Usage of the agent-based system allows simulating human-tutors and students as an interaction between agents where each agent represents a tutor or a student. Similar idea regarding student simulation within ITS has been expressed also in [22, 23], however, student's emotional state is not considered as an important factor during the agent interaction. In our proposed system, the simulation of agents' interaction will be used to evaluate the effectiveness of selected pedagogical agent and its teaching approach (used tutoring strategies) on student's emotional state, behavior and learning progress. Thus the planned agent-based affective tutoring system will be implemented as a simulation system to carry out experiments needed to test different teaching methods and pedagogical approaches, different learning material representations and different ordering of material contents to see how these decisions affect behavior of student's agent.

The system will consist of two types of intelligent agents: a student agent and a tutor agent. Student agent is responsible for collecting and processing information about the human-student (e.g. background knowledge, psychological characteristics, learning progress, problem solving behavior, etc.) to simulate student's behavior, feelings, and reasoning. Tutor agent will represent human-tutor possessing pedagogical knowledge. Agent's main task is related to the implementation of teaching process including decision making about "*when*" to teach by identifying the right intervention moment, "*what*" to teach by choosing suitable tutoring actions, their sequence and content, and "*how*" to teach by selecting appropriate teaching methods [24]. The simulation and decision making will be done in reasoning mechanisms. The main task of student reasoning mechanism is to generate emotion and according behavior. During agent interaction, emotional responses, behavior and reasoning expressed by student's agent will be used as a feedback for the tutor's behavior adaptation, including changes in assigned initial personality, teaching style, emotional characteristics, etc. Tutor reasoning mechanism will have following tasks: (1) to distinguish between simulated and real response from the student, (2) to choose appropriate tutoring strategies, (3) to determine whether the results acquired from student's agent are satisfactory.

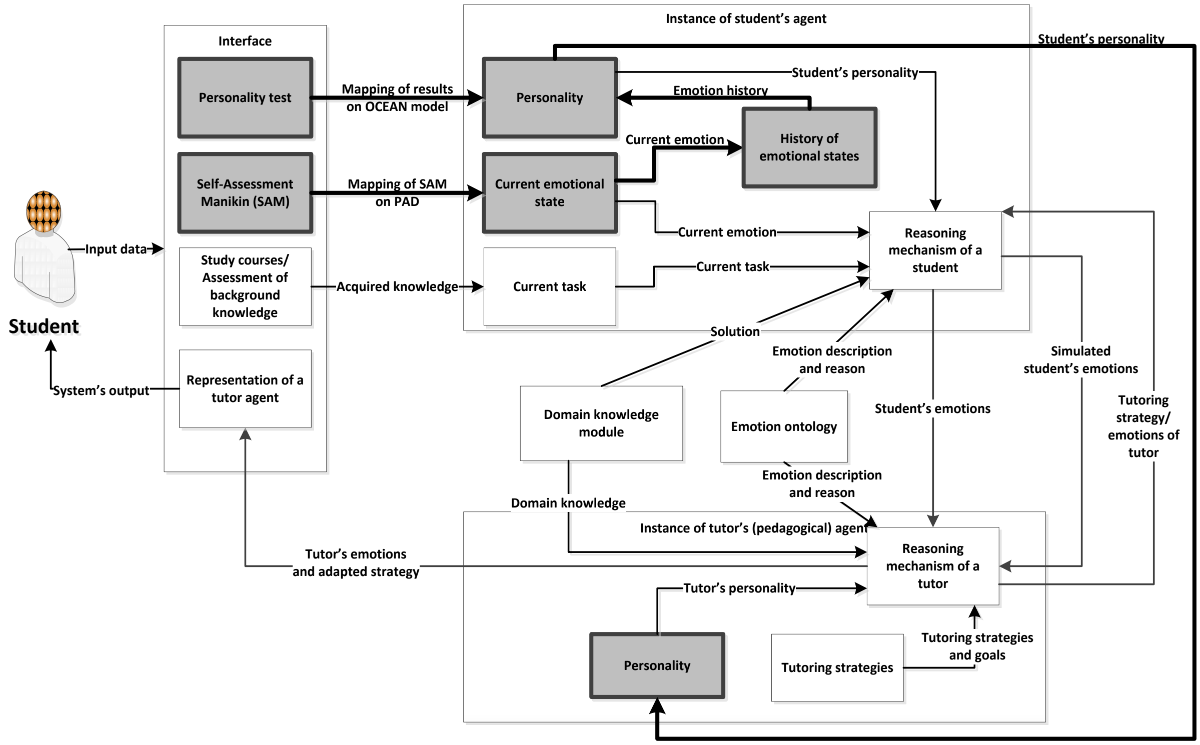

Fig.1. Conceptual architecture of multi-agent based affective tutoring system

Interface will serve as an interaction manager among the system and the student by receiving input data from a student (e.g. self-assessment of affective state, completed personality test, or task solutions) and providing system's output (for example, teaching material, visual representation of a tutor agent, feedback, etc.). Domain knowledge component will store problem domain knowledge intended to be taught using the system. Shared emotion ontology is used so that both involved parties (a student agent and a tutor agent) would understand the emotions of each other. Understanding student's emotions and eliciting factors of student's emotions, would allow tutor agent to learn and as a result adapt better.

Since, regarding emotion modeling one of goals is a creation of a system that would be as non-invasive as possible, then different methods for student's emotion assessment have been analyzed, e.g. emotion identification from action history [25], however, we found that the model acquired from such methods is too simple for generating believable behavior. Also, the model acquired from facial expression recognition can be applied mainly on so-called basic emotions. A few attempts have been made to model more complex emotions, though, the accuracy level is still considered to be too low [26]. Therefore, the Self-Assessment Manikin (SAM) [27] – a non-verbal pictorial assessment technique that directly measures pleasure, arousal, and dominance (PAD) - has been chosen to evaluate student's affect. Application of SAM is intended for student's mood identification at the beginning of every tutoring session with ATS, as well as student's emotion acquisition is planned after completion of a task or block of tasks to evaluate the influence of the teaching process on student's emotional state. In addition, SAM has been implemented as the *AffectButton* for emotion self-report comprising also SAM result (i.e., reported emotion) mapping to PAD values [28].

Student's personality serves as an important factor representing those student's characteristics that are related to consistent patterns of thinking, behaving, and expressing affect, thus influencing the effectiveness of learning/teaching process. Therefore, it is included as one of modeled student's parameters. More detailed relationships between personality, learning/teaching process and affect are described in the next section, explaining personality identification and further application as well. According to the determined student's personality, an appropriate tutor agent will be created with the initial personality, behavior, and teaching style that influence agent's reasoning mechanisms. Matching between student's personality and tutor's personality is represented further in this paper. In general, all currently implemented components are marked in Fig. 1 with dark grey color.

III. Student Emotion Modeling and Tutor's Personality Matching

Emotion modeling in an affective system includes various activities, such as emotion acquisition from the user, emotion synthesis and emotion expression. In the current stage of the research, the focus has been set on emotion acquisition and interpretation. To develop model of user's emotion, various techniques are used. The emotion calculation and modeling in an agent architecture is done by abstract unit called emotion computation model (ECM) [29]. As there will be two agent types in the system, two different ECM will be needed. The functions of user ECM will be emotion acquisition and modeling for simulation purpose. The tutor agent must express and synthesize emotions. The interaction between student and tutor agent will be done in standard agent protocols and thus expression of student's emotions and acquisition of tutor's emotions is not needed.

In this section, the related work in acquisition and modeling of personality and mood is analyzed. The developed components of the system are described as well.

A. Personality

Personality and each person's individual differences are part of daily life and they are expressed in feelings, motivation, behavior, perception, cognition, decision making, etc. [30, 31]. Human personality has been studied for many years by different psychologists, therefore different "personality" definitions have been proposed, e.g. personality "permits a prediction of what a person will do in a given situation" [32] or personality "represents those characteristics of the person that account for consistent patterns of feeling, thinking, and behaving" [33]. Despite various definitions, a common reason for using personality is the acquisition of unique pattern of person's traits allowing predicting and explaining his/her behavior (including emotional reactions, thoughts, and actions).

Although regarding personality, there is no consensus among psychologists on the best way how to describe person's individual differences, many of them supports the Five Factor Model (FFM) or Big Five personality model. FFM is founded on the principle that ways in which people differ in their emotional and attitudinal styles can be summarized with the five basic traits (also called OCEAN) [34, 35]:

- **O**penness – open people demonstrate imagination, innovativeness (like to experience new things), rule breaking and those who score low tend to act more conventionally and have a conservative outlook.
- **C**onscientiousness – conscientious people are responsible, reliable, and tidy. They think about all their behaviors' outputs before acting and take responsibility for their actions.
- **E**xtraversion – extroverts are outgoing, sociable, friendly and assertive. They are described as active, bold, assertive, exciting, stimulating and energetic in achieving their goals. Introverts on the other hand tend to be reserved, even-paced and independent.
- **A**greeableness – agreeable people are trustworthy, kind, unselfish, generous, fair, cooperative, striving for common understanding, and maintaining social affiliations. They consider other people's goals and are ready to surrender their own goals.
- **N**euroticism – neurotic people tend to experience effects such as fear, sadness, embarrassment, disgust, anger, anxiety, and prone to depression. Those who score low in this area are usually calm, moderate-tempered and relaxed at work and in their personal lives. An emotionally stable person recognizes and understands the potential consequences of their different emotional states and is able to regulate and control them.

FFM can be used in different branches of psychology: industrial, organizational, clinical, educational, forensic, and health psychology. Another advantage of the model is that any personality type can be represented through the combination of the five traits, because they are found to be independent from each other [36]. By analyzing already existing research related to the personality's influence on the learning/teaching process, it can be concluded that knowledge about a student's personality (represented as OCEAN values) can be used to identify various factors influencing learning/teaching process:

- student's **default mood** (or temperament) that has an impact on a tendency to particular emotions and their intensity [37];
- student's **learning goals** [38, 39];
- student's **intrinsic motivation** to learn and prone to **academic achievements** [40, 41, 42];
- student's **learning style** [31, 43];
- the most **suitable tutor's personality** and preferences for specific **teaching methods** for particular students depending on their personalities [31, 44].

In general, it is assumed that students would prefer tutors who are emotionally stable (opposite to neuroticism) and conscientious expressing good communication skills, interest into students' questions and showing enthusiasm about their teaching subjects. However, carried out studies reveal that students prefer tutors who are similar to themselves in all personality traits (particularly for openness and conscientiousness) except neurotic students who prefer agreeable tutors [38]. This can also be explained by the fact that in human-human interaction, the personality of each human can influence the relationship satisfaction and each human's perception of the others. This relationship can be explained by the social psychological rule called 'law of attraction' in human-human interaction [45] and there is evidence that the similarity-attraction hypothesis appears also in human-computer interaction [46]. Therefore, studies suggest that preferences for tutor's personality are largely dependent on student's own personality characteristics, showing significant positive correlations between the student's personality traits (FFM dimensions) and those of preferred tutor. One benefit of modeling personality traits is that they can be taken into account when choosing tutoring actions, thus delivering personalized tutoring.

Therefore, studies suggest that preferences for tutor's personality are largely dependent on student's own personality characteristics, showing significant positive correlations between the student's personality traits (FFM dimensions) and those of preferred tutor. One benefit of modeling personality traits is that they can be taken into account when choosing tutoring actions, thus delivering personalized tutoring.

Several rating instruments have been developed to measure the Big-Five dimensions. The most comprehensive instrument is NEO-PI-R measure with 240-item [47] which allows measuring the Big-Five domains and six specific facets within each dimension (taking about 45 min to complete). Since, the NEO-PI-R is too long for many research purposes and often time is limited, researchers may be faced with the choice of using an extremely brief measure of the Big-Five personality dimensions. To meet the need for a very brief measure, different shortened versions for the evaluation of Big-Five personality dimensions have been developed, e.g. Five-Item or Ten-Item Personality Inventories (FIPI and TIPI). However, such measures can sacrifice the reliability and validity of the longer Big Five personality dimensions' measures [48], therefore, for this study, the Mini-IPIP, a 20-item FFM measure with four items per each dimension, was selected for implementation [49]. Mini-IPIP scales measure has acceptable reliability and validity with other Big Five measures. This indicates that the Mini-IPIP is an acceptable and practically useful short measure of the Big Five personality dimensions [50]. Implementation of Mini-IPIP measure to acquire basic student's personality is shown in Fig. 2. The Mini-IPIP test results (acquired OCEAN values) are later used to generate default mood by calculating PAD values.

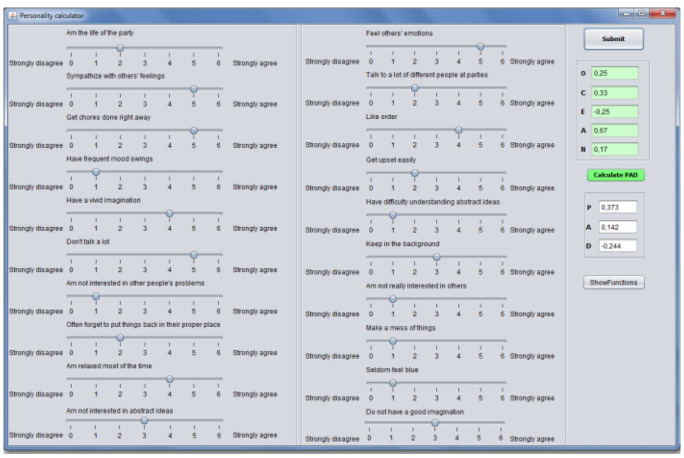

Fig.2. Implemented Mini-IPIP personality measure

B. *Personality, Mood and Emotions*

Emotions, mood (sometimes referred as "temperament" [51]) and personality interact with each other in different ways. Personality remains stable and represents person's long-term traits. Mood and emotions are states closely linked to personality. Moods are differentiated from emotions by intensity and duration. They are considered to be low-intensity long-lasting affective states, whereas emotions are considered high intensity, situation specific, and brief [52]. More precisely, mood is an average of a person's emotional states across a representative variety of life situations [53]. Although many examples can be found in the literature showing how emotions and mood affect decision making [1], personality's role is also essential because of the differences in cognition helping to explain why different people reach different decisions while experiencing the same emotions [54].

Research has shown that FFM dimensions correlate with Pleasure, Arousal and Dominance (PAD) space, proposed by Mehrabian [51]. The advantage of PAD space is that it can combine emotions, mood and personality in one common space, when otherwise they would exist in complete isolation, despite being closely related. That means single emotions can be described in terms of Pleasure, Arousal and Dominance values as well as whole personalities.

FFM personality traits are not only computationally simple (OCEAN values can be acquired using FFM measures) but these values ranging from -1 to 1 can be also mapped to an individual's mood in PAD mood space in a range of [-1, 1] [55]. It allows simulating the influence of personality on emotional states. Formulas (1) are also provided by Mehrabian to convert FFM into PAD space [51].

$$\begin{aligned} P &= 0.21 * E + 0.59 * A + 0.19 * N \\ A &= 0.15 * O + 0.30 * A - 0.57 * N \\ D &= 0.25 * O + 0.17 * C + 0.60 * E - 0.32 * A \end{aligned} \tag{1}$$

These formulas allow acquiring basic mood sometimes referred to as a core affect which influences reflexes, perception, cognition, and behavior and can be caused by many internal and external reasons [56]. The emotions in PAD space can be translated to emotion modeling more directly than personality axis from Five Factor model thus it is used in our affective tutoring system.

C. *Emotion Modeling and Personality Matching*

User emotion modeling mainly consists of three parts: emotion detection, appraisal and decay calculation. In the current stage of the research, we are not very concerned with the detection of what emotion the user is having as it does not greatly depend on personality and would not make a difference in tutor's personality modeling. There are two types of human emotion - primary and secondary emotions [2]. The primary emotions are the ones that emerge without involvement of the mind. Secondary emotions on the contrary appear by evaluating the situation cognitively. Although, e.g., Ekman [57], has named 6 primary emotions, during intensity and decay modeling, it is more important to distinguish whether the emotion is positive or negative, as well as calculate the arousal level instead of naming particular emotion. Kazemifard [58] has also noted that personality impacts how people perceive negative or positive inputs so our current work is evolved within the lines of primary emotion valence and intensity. In the future work, i.e., in student simulation, the secondary emotions will be included as well.

Although there is no common definition of emotions, there are some properties that emotions have and should be taken into consideration when modeling appraisal and intensity. First of all, emotions have a saturation property [2], i.e., emotions cannot grow infinitely. Similarly, the small irritations do not cause emotions at all - so there should be some kind of threshold function. Secondly, Picard [2] defines the property of repeated strikes, i.e., that several small factors cause more powerful emotion than one larger irritation.

There are some developments in which emotion intensity is modeled. In the OCC model, it is considered that the intensity is related to the gap between plan (or the goal) and real situation [59]. The intensity is then input into threshold function to determine which irritations cause emotions. As considerable amount of emotion calculation approaches are based on OCC, majority of implementations uses this approach. Similar approach is used by plan based architectures [60]. However, these intensity functions do not add personality or mood to the equation, although it is very important part of the system. In other developments, such as [52] the personality is taken into consideration, however, the threshold is fixated thus not considering the property of saturation. Gebhard [61] proposes to calculate intensity using PAD model, however, the acquired value represents the intensity independently from negative or positive input. According to Kazemifard [58], intensity and nature of positive and negative emotions differs which also makes sense if one considers personality as well. For the accounted reasons, we propose to model the intensity in two steps: (1) to determine objective strength of irritation and (2) calculate subjective intensity of emotions. These two steps practically correspond to the appraisal and activation functions.

To determine the objective strength, we propose using a simple method: first, evaluate student's background knowledge on a scale from 1 to 10, secondly, evaluate task's difficulty on the same scale. During the test, student sees the difficulty of the task, as well as knows his evaluation. Thus, the objective irritation is calculated by formula below.

$$I(obj) = E(task) - E(background) \tag{2}$$

To calculate the subjective, we propose using sigmoid as Picard has suggested. Parameters of the sigmoid are being changed according to student's personality. The resulting formula for positive emotions is shown in "(3)".

$$I(subP) = \frac{\left(1 - \frac{D+1}{2}\right) - P}{1 + e^{\frac{-20*(x-0,5)}{A+1}}} + \frac{P}{2} \tag{3}$$

The maximum emotion that person is able to feel depends mostly on dominance, however, pleasure influences how much the function will be shifted on the intensity axis. In general - the more dominant person is, the smaller maximal emotional intensity it can acquire. For all of our data ranges, we have assumed that there is possible to have extreme personalities, thus, if calculated dominance is +1, then the person has almost no emotions. The power of constant e determines how steep the function will be. In emotion space that is represented by arousal - how fast the person can be annoyed.

To model negative feelings, there should be small alterations. First, function should be decrescent, and secondly, it should start at the same intensity as people with negative mood tend to accept negative irritations as even worse. The resulting formula for negative emotions is shown in "(4)".

$$I(subN) = \frac{\left(1 - \frac{D+1}{2}\right) - P}{1 + e^{\frac{20*(x-0,5)}{A+1}}} + \frac{P}{2} - \left(1 - \frac{D+1}{2}\right) \tag{4}$$

The decay function is modeled similarly as in [52, 58], by using exponential function. To adapt the function to core mood, we have used the arousal dimension which represents the emotional stability of a person. The positive decay is calculated by the function is shown in "(5)".

$$D = I(subP) * e^{-\frac{A+1}{20}x + t} + \frac{P}{2} \tag{5}$$

The resulting functions for PAD values (0.373, 0.142, -0.344) are in the Fig. 3.

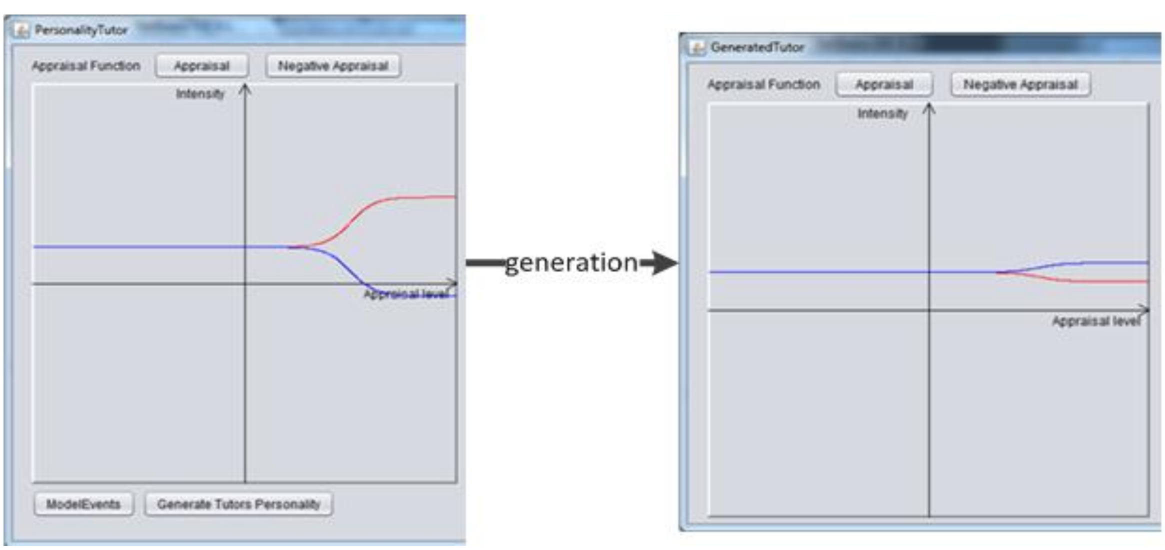

Fig.3. Appraisal functions for student and tutor

The emotions are intertwined in the following way: after the objective intensity is calculated, the result is applied to students personal function, i.e., if the irritation is +5, then the intensity in this case would be about +3. This input is fed into decay function which calculates the intensity value at the time of new irritation.

The tutor modeling is based on generating according functions. The valence (pleasure dimension) and arousal dimension does not differ from students personality, however we have changed the dominance dimension, i.e., the tutor will definitely have dominance of at least 0. If students dominance is $0<D<0.5$, the tutor's dominance will be by 0.5 larger than students dominance. Otherwise the dominance of the tutor equals +1.

The job that has been done in the prototype of the adaptive virtual tutor system will allow modeling users' emotions however there is a lot future work involved.

IV. Conclusion

In this paper, the concept "intelligent tutoring system" and architecture of such systems are briefly described, as well as the multi-agent approach for the development of ITS components is analyzed. Emotion role in the learning process is discussed; however, there still exists a gap for ITSs regarding adaptation skills possessed by human-tutors, particularly, the lack of emotional intelligence. Since, student's personality is closely linked to student's learning, it can serve as an important source for acquiring initial information regarding student's affective state. A conceptual architecture of agent-based ATS for the interaction simulation between human-tutors and students (involving a tutor agent and a student agent) is proposed. This would allow evaluating an influence of different tutor's personalities and their teaching methods on student's emotional state, interest, knowledge acquisition, behavior and learning progress before the implementation of tutoring adaptation to a real student thus assessing the effectiveness of tutor agent's behavior in a timely manner.

Personality is included as one of modeled student's parameters and is determined using Mini-IPIP measure allowing evaluating Five Factor Model personality traits. According to the determined student's personality (acquired OCEAN values) the default mood of a student is modeled and an appropriate personality of a tutor agent is created. We have used a non-invasive method for student mood and personality detection. However, this is ongoing research and these are only the first steps. Future work includes further development of student and tutor emotion models to include several functions, such as emotion synthesis and emotional behavior simulation.

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