

COMBINING TWO DECISION MAKING THEORIES FOR AFFECTIVE LEARNING IN PROGRAMMING COURSES

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Keywords: Affective learning, Bi-Modal Interaction, Multi-Criteria Decision Making.

Abstract: Recently it has been widely acknowledged that the recognition of emotions of computer users can provide more user friendly systems and eventually increase the productivity of users. User friendly interfaces are even more important for the design of educational software that is appropriate for young children. In human-human interaction the expression of emotions of people can be evident in different modes of interaction, such as in speech, in body language, and in facial expressions. In human-computer interaction evidence about the users' emotional states can be drawn by the input devices each user uses for his/her interaction with a computer. In this paper we describe how two decision making theories have been combined in order to provide emotional interaction in an educational application. The resulting educational system is targeted to young children that are taught the basic principles of programming through our own implementation of a programming language called AffectLOGO.

1 INTRODUCTION

Recent advances in human-computer interaction indicate the need for user interfaces to recognise emotions of users while they interact with the computer. For example, (Hudlicka, 2003) points out that an unprecedented growth in HCI has led to a redefinition of requirements for effective user interfaces and that a key component of these requirements is the ability of systems to address affect. This is especially the case for computer-based educational applications that are targeted to children that are in the process of learning. Learning is a complex cognitive process and it is argued that how people feel may play an important role on their cognitive processes as well (Goleman, 1981). At the same time, many researchers acknowledge that affect has been overlooked by the computer community in general (Picard and Klein, 2002).

A remedy in the problem of effectively teaching children through educational applications may lie in rendering student-computer interaction more human-like and affective. To this end, the incorporation of

speaking, animated personas in the user interface of the educational application can be quite important. Indeed, the presence of animated, speaking personas has been considered beneficial for educational software (Johnson et. al., 2000, Lester et. al., 1997).

In view of the above, in this paper we present an affective educational system for children where the basic principles of programming are being taught. In the past, one of the first attempts to teach programming to children was made with the creation of the well-known "Logo" programming language.

The first "Logo" programming language was created in 1967 (Frazier, 1967). The objective was to create a friendly programming language for the education of children where they could learn programming by playing with words and sentences. A detailed study on the "Logo" programming language from its early stages and also recent work on Logo-derived languages and learning applications can be found in (Feurzeig, 2010). For the purposes of our research, the authors have created their own implementation of the "Logo" programming language by incorporating affective interaction into the existing user interfaces.

The resulting educational system is called AffectLOGO and is an affective educational software application targeted to children between the ages of 10 and 15. By using AffectLOGO, children as students can learn basic principles of programming while at the same time their interaction with the computer can be accomplished either orally (by using the computer's microphone), or traditionally by using the computer's keyboard and mouse. At the same time, an animated interactive pedagogical agent is present in order to make the interaction more human like and thus more affective and entertaining.

The system uses the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Hwang & Yoon, 1981), which is a decision-making model. TOPSIS is based on the concept that "the chosen alternative should have the shortest distance from a positive-ideal solution and the longest distance from a negative-ideal solution". So, it calculates the relative Euclidean distance of the alternative from a fictitious ideal alternative. The alternative closest to that ideal alternative and furthest from the negative-ideal alternative is chosen best.

In the system, we use TOPSIS in order to identify the alternative actions that are closest to an ideal alternative action. The selection of the best alternative action is a multi-criteria decision making problem as there are many criteria to be taken into account.

The main body of this paper is organized as follows: In section 2 we present decision making aspects. In sections 3 and 4 we describe the overall functionality and architecture of our system. In section 5 we present our approach in combining evidence from the two modes of interaction using a multi-criteria decision making method in the context of the educational application. Finally, in section 5 we give the conclusions drawn from this work.

2 DECISION MAKING ASPECTS

A multi-attribute decision problem is a situation in which, having defined a set A of actions and a consistent family F of n attributes g_1, g_2, \dots, g_n ($n \geq 3$) on A, one wishes to rank the actions of A from best to worst and determine a subset of actions considered to be the best with respect to F (Vincke, 1992). In traditional methods such as the Simple Additive Weighting (SAW) (Fishburn, 1967, Hwang & Yoon, 1981), the alternative actions are ranked by

the values of a multi-attribute function that is calculated for each alternative as a linear combination of the values of the n attributes. Unlike SAW, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) calculates the relative Euclidean distance of the alternative from a fictitious ideal alternative. The alternative closest to that ideal alternative and furthest from the negative-ideal alternative is chosen best. More specifically, the steps that are needed in order to implement the technique are:

1. *Scale the values of the n attributes to make them comparable.*
2. *Calculate Weighted Ratings.* The weighted value is calculated as: $v_{ij} = w_i \cdot r_{ij}$, where w_i is the weight and r_{ij} is the normalised value of the i th attribute.

3. *Identify Positive-Ideal and Negative-Ideal Solutions.* The positive ideal solution is the composite of all best attribute ratings attainable, and is denoted:

$A^* = \{v_1^*, v_2^*, \dots, v_i^*, \dots, v_n^*\}$ where v_i^* is the best value for the i th attribute among all alternatives. The negative-ideal solution is the composite of all worst attribute ratings attainable, and is denoted:

$A^- = \{v_1^-, v_2^-, \dots, v_i^-, \dots, v_n^-\}$ where v_i^- is the worst value for the i th attribute among all alternatives.

4. *Calculate the separation measure from the positive-ideal and negative-ideal alternative.* The separation of each alternative from the positive-ideal solution A^* , is given by the n -dimensional Euclidean distance:

$$S_j^* = \sqrt{\sum_{i=1}^n (v_{ij} - v_i^*)^2}$$

where j is the index related to the alternatives and i to one of the n attributes. Similarly, the separation from the negative-ideal solution A^- is given by

$$S_j^- = \sqrt{\sum_{i=1}^n (v_{ij} - v_i^-)^2}$$

Calculate Similarity Indexes. The similarity to positive-ideal solution, for alternative j , is finally given by $C_j^* = \frac{S_j^-}{S_j^* + S_j^-}$ with $0 \leq C_j^* \leq 1$. The alternatives

can be ranked according to C_j^* in descending order.

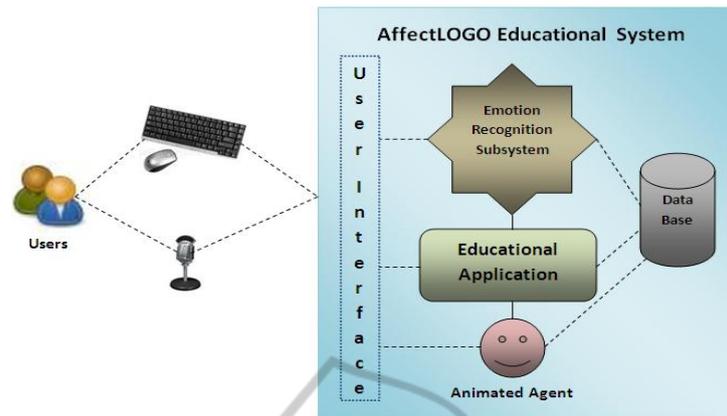


Figure 1: Architecture of the Affectlogo Educational System.

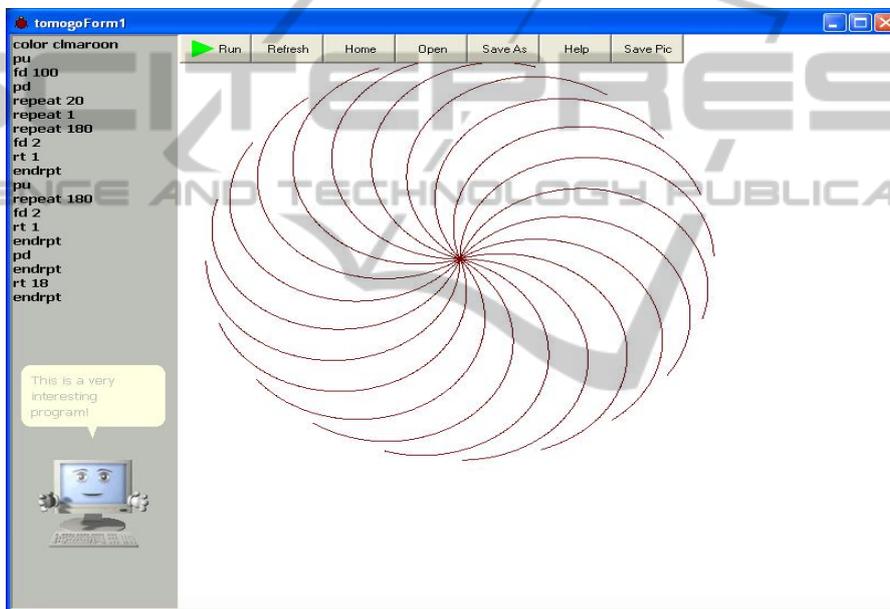


Figure 2: A snapshot of the AffectLOGO educational system.

3 OVERVIEW OF THE SYSTEM

In this section, we describe the overall functionality and emotion recognition features of AffectLOGO. The architecture of AffectLOGO consists of the main educational application, a user monitoring component, emotion recognition inference mechanisms and a database. Part of the database is used to store educational data and data related to the pedagogical agent. Another part of the database is used to store and handle emotion recognition related data. Finally, the database is also used to store user models and user personal profiles for each individual user that uses and interacts with the system. The systems architecture is illustrated in figure 1. As we

can see in figure 1, the students' interaction can be accomplished either orally through the microphone, or through the keyboard/mouse modality. The educational system consists of three subsystems, namely the emotion recognition subsystem, the educational application subsystem and the subsystem that reasons and handles the animated agent's behaviour.

While using the educational application from a desktop computer, students are being taught a particular programming course. The information is given in text form while at the same time an animated agent reads it out loud using a speech engine. Students are prompted to write programming commands and also programs in the AffectLOGO

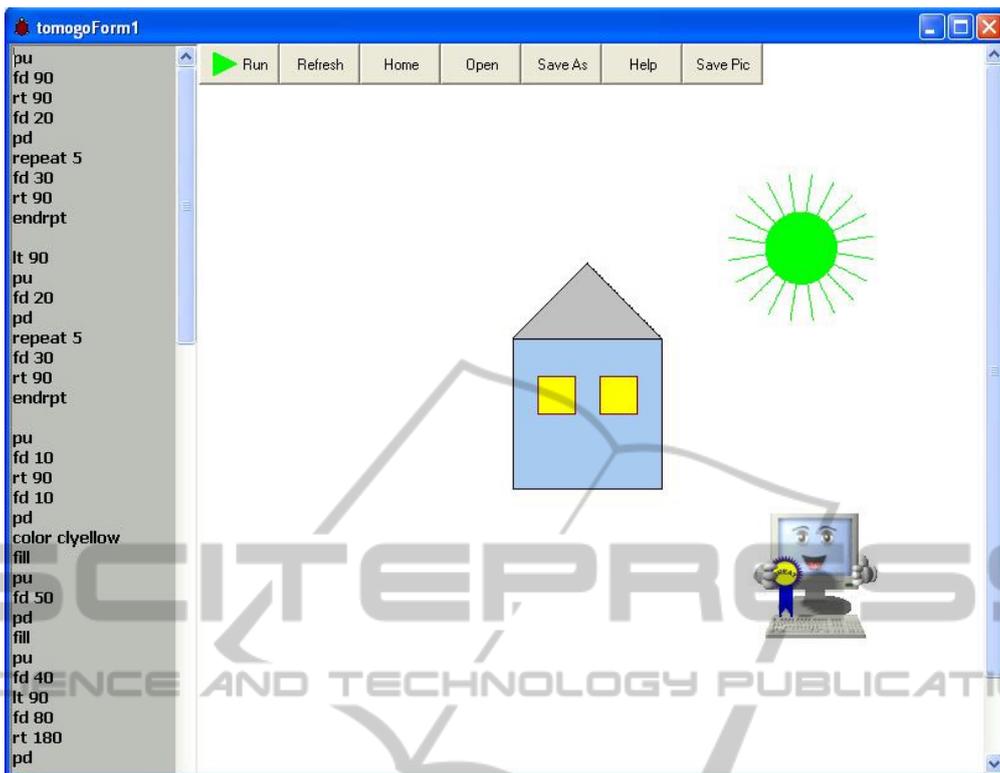


Figure 3: Successful completion of an exercise and reward by the animated agent.

language in order to produce drawings and particular shapes. The main application is installed either on a public computer where all students have access, or alternatively each student may have a copy on his/her own personal computer. An example of using the main application is illustrated in figure 2. The animated agent is present in these modes to make the interaction more human-like.

As it is illustrated in figure 2, a user has accomplished writing a quite complicated program that uses nested loops in order to produce a specific drawing. Figure 3 also illustrates a user who has completed creating a drawn house and a sun by providing the educational system the correct programming commands in the AffectLOGO language. This student's achievement is awarded by a characteristic animation of the agent who also congratulates the student. In such cases, the student who is actually a child between the ages of 10 and 15 is also expected to interact emotionally and in our example the student may express his/her happiness for his/her success in completing correctly a programming exercise.

While the students interact with the main educational application a monitoring component records silently on the background their actions from the keyboard and the microphone interaction and

interprets them in terms possibly recognized emotions. The basic function of this component is to capture all the data inserted by the students either orally or by using the keyboard and the mouse of the computer. The data is recorded to a database and then returned to the basic application the user interacts with. Figure 4 illustrates the "monitoring" component that records the user's input and the exact time of each event.

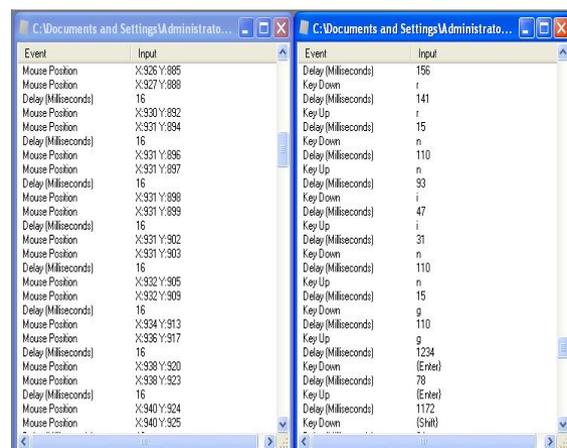


Figure 4: A user-monitoring component recording all user input actions.

As a next step, all recorded user input actions are translated in terms of discrete input actions related to the microphone and to the keyboard. The human experts of the empirical study (Alepis et al 2007) have identified which input action from the keyboard and the microphone could led them in the successful recognition of possible emotional states. From the input actions that appeared in the experiment we have used those that were proposed by the majority of the human experts.

In particular considering the keyboard we have:
 a) a student types normally b) a student types quickly (speed higher than the usual speed of the particular user) c) a student types slowly (speed lower than the usual speed of the particular user) d) a student uses the backspace key often e) a student hits unrelated keys on the keyboard f) a student does not use the keyboard.

Considering the students' basic input actions through the microphone we have 7 cases: a) a student speaks using strong language b) a student uses exclamations c) a student speaks with a high voice volume (higher than the average recorded level) d) a student speaks with a low voice volume (low than the average recorded level) e) a student speaks in a normal voice volume f) a student speaks words from a specific list of words revealing an emotion g) a student does not say anything.

4 ANIMATED AGENTS

Elliot et al. (Elliot, 1999) suggest that animated agents in an educational environment will be more effective teachers if they display and understand emotions. More specifically they point out that:

1. An animated agent should appear to care about students and their progress
2. An animated agent should be sensitive to the student's emotions
3. An animated agent should foster enthusiasm in the student for a subject matter
4. An animated agent may make learning more fun

However, even if new multimodal capabilities like 3D-video and speech synthesis have made pedagogical personas more human-like, there is also a great need in determining "how" (what exactly should the pedagogical persona do) and "when" (in which situation) an animated agent should act/ behave in each part of the tutoring process.

An expected contribution of our system is to affect positively the educational process of students

who learn programming languages. More specifically, the system should motivate the students for the purpose of learning more efficiently and also more enjoyable. In (Soldato and Du Boulay, 1995) it is suggested that a tutoring system must react with the purpose of motivating distracted, less confident or discontented students, or sustaining the disposition of already motivated students.

At the same time a system's critical long-term objective is to operate as an educational tool that implements affective functionalities in order to assist teachers in using user-friendlier, thus more communicable, educational e-learning applications.

In view of the above our system also incorporates an affective module that relies on animated agents. The system models possible emotional states of users-students and proposes tactics for improving the interaction between the animated agent and the student who uses the educational application. The system may suggest that the animated agent should express a specific emotional state to the student for the purpose of motivating her/him while s/he learns. Accordingly, the agent becomes a more effective teacher. Table 1 illustrates event variables that are used as triggers for the activation of the animated agents. Each time a trigger condition takes place the animated agent uses a certain tactic in order to communicate emotionally with the user for pedagogical reasons.

Table 1: Event variables for the activation of animated agents.

Event variables
<ul style="list-style-type: none"> • a mistake (the user may receive an error message by the application or navigate wrongly) • many consecutive mistakes • absence of user action for a period of time • action unrelated to the main application • correct interaction • many consecutive correct answers (related to a specific test) • many consecutive wrong answers (related to a specific test) • user aborts an exercise • user aborts reading the whole theory • user requests help from the persona • user takes a difficult test • user takes an easy test • user takes a test concerning a new part of the theory • user takes a test from a well known part of the theory

5 APPLICATION OF THE COMBINATION OF THE TWO DIFFERENT DECISION MAKING METHODS

For the evaluation of each alternative emotion the system uses as criteria the input actions that are relate to the emotional states that may occur while a student interacts with our educational system. These input actions were described in the previous section and are considered as criteria for evaluating all different emotions and selecting the one that seems to be prevailing. More specifically, the system uses a novel combination of TOPSIS and SAW for a particular category of users. This particular category comprises of the young students (between the ages of 10 and 15) and who are novice in programming courses.

In order to find out which emotion is more likely to have been felt by the user interacting with the system, we use TOPSIS. More specifically, we use the specific multi-criteria decision making theory for combining evidence from the two different modes and finding the best indication. More specifically, we want to combine em_{1e_1} and em_{1e_2} . em_{1e_1} is the probability that an emotion has occurred based on the keyboard actions and em_{1e_2} is the probability that refers to an emotional state using the users' input from the microphone. These probabilities result from the application of the decision making model of SAW and are presented below. em_{1e_1} and em_{1e_2} take their values in [0,1].

$$em_{1e_1} = w_{1e_1k_1}k_1 + w_{1e_1k_2}k_2 + w_{1e_1k_3}k_3 + w_{1e_1k_4}k_4 + w_{1e_1k_5}k_5 + w_{1e_1k_6}k_6$$

Formula 1.

$$em_{1e_2} = w_{1e_2m_1}m_1 + w_{1e_2m_2}m_2 + w_{1e_2m_3}m_3 + w_{1e_2m_4}m_4 + w_{1e_2m_5}m_5 + w_{1e_2m_6}m_6 + w_{1e_2m_7}m_7$$

Formula 2.

In formula 1 the k 's from k_1 to k_6 refer to the six basic input actions that correspond to the keyboard. In formula 2 the m 's from m_1 to m_7 refer to the seven basic input actions that correspond to the microphone. These variables are Boolean. In each moment the system takes data from the bi-modal

interface and translates them in terms of keyboard and microphone actions. If an action has occurred the corresponding criterion takes the value 1, otherwise its value is set to 0. The w 's represent the weights. These weights correspond to a specific emotion and to a specific input action and are acquired by the stereotype database. More specifically, the weights are acquired by the stereotypes about the emotions.

In a previous related work (Alepis et al. 2007), the combination of the two modes was accomplished by calculating the mean of the likelihood of every emotion of the two modes. However, this way of calculation was simple and did not combine effectively the evidence from the two modes. Therefore, in this paper we check the efficiency of TOPSIS for combining effectively the evidence from two modes.

TOPSIS is based on the concept that "the chosen alternative should have the shortest distance from a positive-ideal solution and the longest distance from a negative-ideal solution". Therefore, the system first identifies the Positive-Ideal and the Negative-Ideal alternative actions taking into account the criteria that were presented in the previous section. The Positive-Ideal alternative action is the composite of all best criteria (in this case the mode plays the role of criteria) ratings attainable, and is denoted: $A^* = \{em_{1e_1}^*, em_{1e_2}^*\}$ where

$em_{1e_1}^*, em_{1e_2}^*$ are best values of the modes among all alternative emotions. The Negative-Ideal solution is the composite of all worst attribute ratings attainable, and is denoted: $A^- = \{em_{1e_1}^-, em_{1e_2}^-\}$ where $em_{1e_1}^-, em_{1e_2}^-$ are the worst values for the modes among all alternative emotions.

For every alternative action, the system calculates the Euclidean distance from the Positive-Ideal and Negative-Ideal alternative. For the j alternative emotion, the Euclidean distance from the Positive-Ideal alternative is given by:

$$S_j^* = \sqrt{(em_{1e_1j} - em_{1e_1}^*)^2 + (em_{1e_2j} - em_{1e_2}^*)^2}. \quad \text{The}$$

Euclidean distance from the Negative-Ideal alternative is given by the formula:

$$S_j^- = \sqrt{(em_{1e_1j} - em_{1e_1}^-)^2 + (em_{1e_2j} - em_{1e_2}^-)^2}.$$

Finally, the value of the likelihood for the alternative emotion j , is given by the formula

$$lem_j^* = \frac{S_j^-}{S_j^* + S_j^-} \quad \text{with } 0 \leq lem_j^* \leq 1 \quad \text{and shows how}$$

similar the j alternative is to the ideal alternative

action A^* . Therefore, the system selects the alternative emotion that has the likelihood (lem).

6 CONCLUSIONS

In this paper we have shown a novel combination of two different decision making theories for emotion recognition in a learning environment. More specifically, the system uses SAW for estimating the result of each mode and TOPSIS for combining the results of the two modes and find the emotion that is more likeable to have been felt by young children as users of the resulting system.

It is in our future plans to evaluate AffectLOGO in order to examine the degree of usefulness of the educational tool for the teachers, as well as the degree of usefulness and user-friendliness for the students who are going to use the educational system.

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