Predicting Learners' Emotional Response in Intelligent Distance Learning Systems

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Abstract

Different research studies have proved that emotions meet a pivotal role in cognitive processes and in particular the studies made by Damasio who argues that human-beings without emotions could not make the simplest decision (Damasio 1994). We think that the fail of Intelligent Distance Learning Systems to achieve an efficient learning is mainly resulting from the lacking of Emotional Intelligence abilities. These systems require a capacity to manage the emotional state of the learner so as to be in the best conditions for learning. To achieve this goal, it is very important to anticipate the emotional response of the learner after the happening of an event in the learning session.

In this paper, we propose a method for predicting the learners' emotional response by using an intelligent agent called ERPA (Emotional Response Predictor Agent). This agent uses a case-based reasoning, an Artificial Intelligence technique, and a Learner's Event-Appraisal Model.

Introduction

For several years e-learning systems have known a very significant evolution with the passing of years. Previously they were simple systems lacking of the intelligence. More and more now these systems acquire new forms of intelligence while making it possible to adapt the learning activity to the level of the learner's knowledge. In fact, there are different types of intelligence which are classified, generally, in two categories, the *abstract intelligence* and the *practical intelligence*. The abstract intelligence corresponds to the ability to understand and handle ideas or abstract concepts, whereas the practical intelligence corresponds to the ability to react in front of events which take place outside the school context (Wagner 2000). The practical intelligence is composed of two forms of intelligence: *mechanical intelligence* and *social intelligence*. The mechanical intelligence corresponds to the ability to understand and handle objects whereas the social intelligence corresponds to the ability to interact socially with other people. Recently new form of the social intelligence appeared called the *emotional intelligence* (Goleman 1995). Mayer and Salovey defined the emotional intelligence as the ability: *to perceive, evaluate and express emotions that improve the reasoning, to understand the emotions and emotional knowledge and to control the emotions in order to support the emotional and intellectual growth* (Mayer and Salovey 2000). From this definition, we can conclude that emotional intelligence is very important in the learning context and necessary for the tutor. In the classroom, the teacher who has emotional intelligence abilities could maintain attention and learners interest by making a joke for example when he feels that his students are bored, so he tried to manage their emotional state in order to keep a good atmosphere for learning. These capacities of the emotional intelligence are deprived in intelligent distance learning systems. This is one of the reasons which prevent these systems from reaching an efficient learning. So these systems require a capacity to manage the emotional state of the learner. This ability consists in pursuing the emotional profile of the learner and to intervene when it is necessary. Finding the emotional profile of the learner requires tracing his emotional state from the beginning of the learning activity. With the emotional profile of the learner, the system will be able to know what's the intervention strategy could it use to improve the emotional state and which is the best time to intervene, aiming to set the learner under the best emotional conditions of learning (Chaffar and Frasson 2005). To construct the emotional profile of the learner, we need to predict his emotional response. So, how can we predict his emotional response?

In this work, we present an agent called ERPA (Emotional Response Predicting Agent). ERPA uses a method for predicting the emotional response of the learner using the Case-Based Reasoning (CBR) technique and a Learner's Event-Appraisal Model inspired by the OCC model (Ortony, Clore, and Collins 1988).

This paper begins with a survey of previous work realized and interested in computational models of emotions. Next, we discuss some appraisal theories that exist and present a Learner's Event-Appraisal Model inspired by the OCC model (Ortony, Clore, and Collins 1988). After that, in the section 3, we present the ERPA, an agent for predicting the learners' emotional response. In the same section, we present first some basic elements of the CBR technique, second the architecture of the ERPA agent and third we discuss the strategy used by the ERPA. In the section 4, we show an experiment that we have developed to initialize the case-base for predicting the emotional response of the learner. Finally, we conclude the paper and present the studies that we project to do in the future.

Previous Work

Various research studies argue that emotions play a crucial role in decision-making, cognitive processes and performance (Damasio 1994; Goleman 1995; Isen 2000). According to studies made by Damasio, without emotions human beings are not able to make the simplest decision (Damasio 1994). Analogically some researchers consider that the information processing systems also cannot then make good decisions without emotions. Indeed, Sloman thinks that intelligent machines should essentially experience emotion (Sloman and Croucher 1987). Moreover, Mavin Minsky confirms that "*The question is not whether intelligent machines can have emotions, but whether machines can be intelligent without any emotions*" (Minsky 1985).

In the same perspective, some Artificial Intelligence (AI) researchers have put an interest in computational models of emotions and especially in the agent research community. So, a large amount of research has been interested in embedding computational models of emotions in virtual agents. For instance, Seif el-Nasr and colleagues proposed a new computational model of emotions that can be integrated in intelligent agents. This model uses fuzzy-logic to represent events and observations to emotional states (Seif El-Nasr, Yen, and Ioerger 2000). In addition, Gratch and Marsella proposed a model for deriving emotion and for informing a number of the behaviors that must be modeled by virtual humans like facial expressions, planning, etc. (Gratch and Marsella 2004). Moreover, Reilly and Bates used the event-appraisal model of Ortony and colleagues (Ortony, Clore, and Collins 1988**)** to develop believable agents within the OZ project. These agents are able to express emotions after evaluating the impact of an event on the agent's goals (Reilly and Bates 1992). However, (Rehm and André 2005) research was focused on synthetic agents that should express emotions which are in conflict with their appraisal process.

Besides, in the learning context, Lester and colleagues created a pedagogical agent called Cosmo. This agent is able to show emotive behaviors in the purpose to support learners in problem-solving activities (Lester, Towns, and FitzGerald 1999). Nkambou and colleagues, in the same context, proposed a platform for pedagogical affective agents in which they presented two agents one is for recognizing emotions and the other is for expressing them (Nkambou, Héritier, and Frasson 2005). Also in a learning context, Lisetti and colleagues have implemented a model for the affective state of the avatar based on the Belief Desire Intention architecture (Paleari, Lisetti, and Lethonen 2005).

In MIT media lab Picard and colleagues proposed a model that describes the changing of the emotional state during model-based learning experiences, to aid efficient learning (Kort, Reilly, and Picard 2001). In the best of our knowledge, few works have been interested in modeling the learners' emotional state. Thus the aim of this research is to predict the learners' emotional response using computational models of emotions and the CBR technique. Our approach is based on the event-appraisal model of emotions, proposed by Ortony, Clore and Collins (OCC) (Ortony, Clore, and Collins 1988**)**, and consists in modeling the learners' event-appraisal process.

The Learner's Event-Appraisal Model

According to appraisal theorists emotions are exhibited as a consequence of certain interpretations and events appraisals. Appraisal, as defined by Sellers and Peterson, "*determines one's reactions to an event, including attempts to cope with it*" (Sellers and Peterson 1993). In the purpose to predict emotion elicitation, some theorists in psychology have developed different event-appraisal models of emotions. Each one has defined different number and types of appraisal criteria and a set of emotions to cover. Roseman's model, for example, defines 5 criteria of event evaluation which, according to their values, identify 13 distinct emotions (Roseman 1991). For the OCC model Ortony, Clore and Collins (1988) have defined three aspects which could cause emotional reactions: consequences of events, actions of agents or aspects of objects and they specified 22 emotion types. These emotion types were classified according to the three aspects. For the emotion types elicited by the consequences of events, the authors have distinguished between consequences for other and consequences for self. In our work, we are focusing only on events that have consequences for self and could modify user's own emotions. So we define a set of eight emotions (Joy, Distress, Hope, Satisfaction, Fears-confirmed, Disappointment, and Relief) and for each one we associated the rule which might cause it (see Table 1). For example, a learner has passed an evaluation test and he is waiting for the result, if we suppose that he has passed the test well and he expects to have a good mark greater than 15/20 and less than 17/20. So, this situation may cause *hope* as emotional response to the expected event. After that, suppose that this learner has obtained 18/20 in the test, this event may cause to him a *satisfaction* for having a mark greater than 15, it may also cause *joy* because the learner doesn't expect to obtain a mark greater than 17.

Emotion Type	**Rule**
Joy	Happening of a desirable event.
Distress	Happening of an undesirable event.
Hope	Waiting a prospected desirable event.
Fear	Waiting a prospected undesirable event.
Satisfaction	Happening of the prospected desirable event.
Fears-confirmed	Happening of the prospected undesirable event.
Disappointment	Not happening of the prospected desirable event.
Relief	Not happening of the prospected undesirable event.

Table 1. The learner's event appraisal rules

The table above shows the set of rules that might trigger an emotion; in the next section, we explain how we use these rules for predicting the learners' emotional response.

The Emotional Response Predictor Agent (ERPA)

Since the emotional response is an individual mechanism which depends on the human experience, culture, age, etc., we have thought to integrate the CBR technique in the ERPA agent, in the purpose to consider other criteria in addition to the rules identified previously.

The CBR Technique

This AI technique tries to find a solution for a problem by searching a similar problem in the case-base, taking the solution of the past problem and using it to find a solution for the present problem. A case in the case-base is considered as a past experience that has been resolved and it is composed of two parts: the case description and the solution associated to the case. Aamodt and Plaza in 1994 have defined the CBR as a cyclical process (see Figure 1).

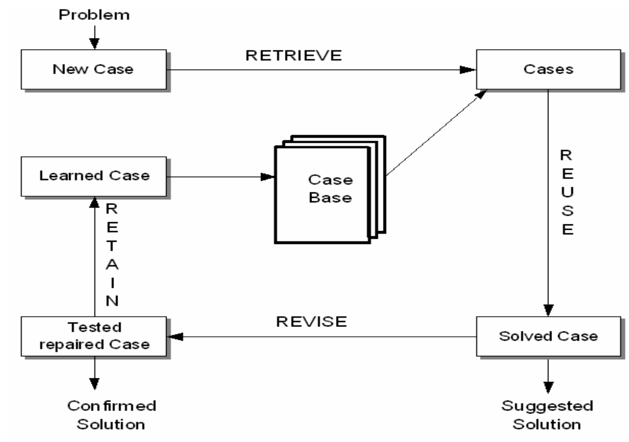

Figure 1. The CBR cycle (Aamodt and Plaza 1994)

As shown in the figure above, the cyclical process of the CBR is composed of 4 steps:

- The retrieval phase: it consists in searching the most similar cases of the case-base to the new problem to be solved.
- The reuse phase: it consists in taking the solution of the case selected in the preceding phase, and to adapt it for the new problem.
- The revise phase: it consists in checking if the solution suggested can solve the problem or it requires new modifications.
- The retain phase: in this phase the new solution is retained in the case-base.

To predict the emotional response of the learner, several things require to be taken into account and essentially the individual differences, the initial emotional state and the event occurred that might change this emotional state. For this reason, the ERPA agent uses the CBR technique in which the case description represents some individual differences criteria (age, sex, nationality, and personality), the initial emotional state and the event occurred. The solution associated to the case description represents the learner's emotional response.

The ERPA Architecture

The architecture of the ERPA presented in the Figure 2 is a three tiers architecture that consists of a User Interface Tier, an Application Tier and a Data Base Tier.

- The User Interface Tier: it represents the interfaces by which the ERPA agent interacts with the learner.

- The Application Tier: this component corresponds to the strategy exploited by the agent to forecast the emotional response of the learner.
- The Data Base Tier: it represents the case-base in which the ERPA agent stores the cases.

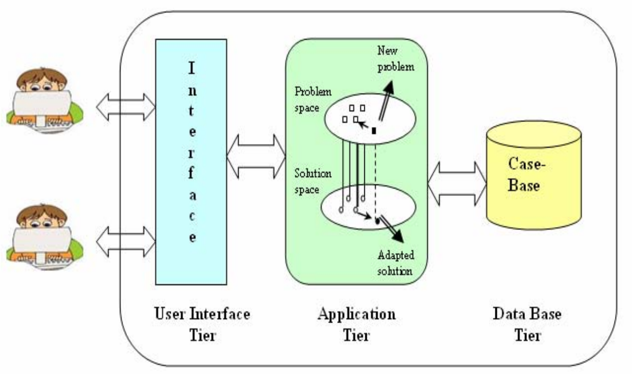

Figure 2. The ERPA architecture

The Application Tier of the ERPA agent architecture will be explained more in detail in the next section.

The ERPA Strategy

The strategy used to predict the emotional response of the learner proceeds in the Application Tier. It consists in using the CBR technique and the learner's event appraisal rules that we have previously identified (see Table 1).

Suppose that the set of events that might arise during a learning session is noted by E and each event occurred at time i is noted by e_i. We are attempting to predict r_i, the emotional response that occurred after a given event e_i has aroused. When a new problem arises to find r_i, it is transformed into target case of which the description part of the case uses the same formalism of representation as that used by the sources cases stored in the case-base. The solution part of the target case is built by seeking among the sources cases those of which the description of the case is the most similar to the description of the target case. To calculate this similarity, the ERPA uses the k-nearest-neighbors in which the similarity between two cases c and q is defined as:

$$S(c, q) = \sum w_i S_i(c_i, q_i) \ . \qquad \textbf{(1)}$$

Where:
c_i = the attributes of the case c.
q_i = the attributes of the case q.
S_i = the different similarities of the attributes.
w_i= the weights associated to the attributes.

The cases, in the case-base used by the ERPA are represented as a couple of problem and solution. The problem in the case-base is represented in the form of a vector of *n* attributes and the solution is constituted by a vector of *m* attributes as shown bellow:

$$\left(\langle att_1, att_2, ..., att_n \rangle, \langle att_1, att_2, ..., att_m \rangle\right) .$$

The problem in the present application represents the learner with a set of attributes defined as: nickname, age, sex, nationality, personality, initial emotion, and event. We have identified different classes of ages: [15-25], [25-35], [35-45], etc. For each attribute identified previously, a weight w_i is respectively associated: 0.0, 0.1, 0.1, 0.1, 0.1, 0.3, and 0.3. So, the largest value of w_i is associated to the initial emotion and to the event occurred. These weights are valid only for calculating the similarities between two cases. For example if we have a problem case *p1* defined as:

$$\langle Eternel, 34, male, canadian, Extravert, fear, 12 \rangle$$

and a case *p2* defined as:

$$\langle Souma, 28, Female, tunisian, Extravert, fear, 15 \rangle$$

$$\begin{aligned} S(P1, P2) &= (0.0 * 0) + (0.1 * 1) + (0.1 * 0) + (0.1 * 0) \\ &+ (0.1 * 1) + (0.3 * 1) + (0.3 * 1) = 0.8 \end{aligned}$$

So, the similarity rate for the participants named Eternel and Souma is 80 %.

The solution is represented by a unique attribute which is the learner's emotional response r_i. An example of case representation is given in the next section (see Figure 4).

Initializing the Case-Base

To fill the case-base with an initial set of cases, we set up an experiment in which 52 participants have introduced the nickname, the age, the sex, and the nationality in the aim to build the attributes of the case problem. Next, the participants have to answer to the Abbreviated form of the Revised Eysenck Personality Questionnaire (EPQR-A) for identifying their personality traits (Francis, Brown, and Philipchalk 1992). After that, they have to pass an evaluation test which consists in answering ten questions in algorithm and data structure. After passing the test, we ask them if they expect to succeed in the test or not. To affect a value to the initial emotion attribute, we proceeds as follow:

IF Expect (learner, succeed) is TRUE
THEN initial_emotion = HOPE
ELSE initial_emotion = FEAR

We also ask the participants to enter the mark that they expect to obtain, and then we give them the result. Next, after having obtained the mark, they have to choose the emotions that they feel following the occurrence of this event (see Figure 3) from a set of 6 emotions (Joy, Distress, Satisfaction, Fear-confirmed, Relief, and Disappointment).

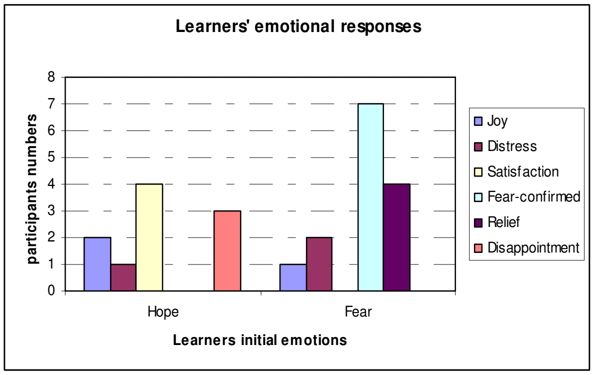

Figure 3. Learners' emotional responses

With all the attributes mentioned previously (nickname, age, sex, nationality, personality, initial emotion, and event), we construct the case (see Figure 4) and we store it in the case-base.

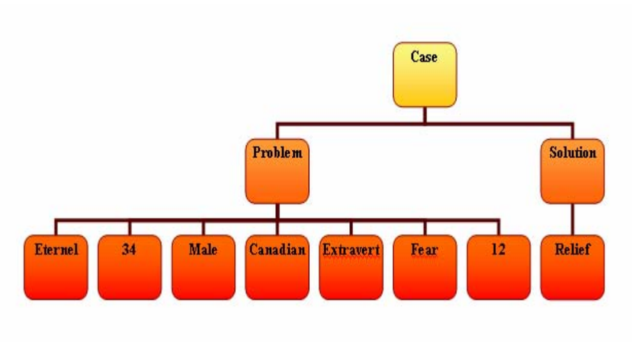

Figure 4. Example of a case in the case-base

This tree shows an example of case that we have obtained from the experiment. It demonstrates a participant named *Eternel*, his age is 34, he is a Canadian and has an extravert personality which is found by applying the EPQR-A questionnaire (Francis, Brown, and Philipchalk 1992). After passing the evaluation test, he expects that he wouldn't succeed to the test, but fortunately he obtains 12/20 and succeeds. So he feels relieved.

All these cases will be useful, as a starting point, to predict the learners' emotional responses, by calculating the similarity between two cases with equation (1). So, the predicted emotion will be the solution of the most similar case.

Conclusion and Future Research

Since emotions are widely related to cognitive processes, Intelligent Distance Learning Systems should consider these affective states. They play a fundamental role in maintaining the attention of the learner and in improving his reasoning and performance. For this reason, this research is focused on the learners' affective state.

This research work is interested in predicting the learners' emotional response in Intelligent Distance Learning Systems. To this end, we have proposed a method in which we used the CBR technique and some learners' event-appraisal rules that we have identified basing on the OCC model (Ortony, Clore, and Collins 1988**)**. After predicting the learner's emotional response, the system will require a strategy by which it could change his emotional state like the one used in (Chaffar and Frasson 2004). So, in the next step we will concentrate on the intervention strategies to choose the best one depending on individual differences.

Moreover, in this work we are limited, for the moment, in a set of 8 emotions (Joy, Distress, Hope, Fear, Satisfaction, Fear-confirmed, Relief, and Disappointment). For the future, we plan to cover more other emotions which are related, in the OCC model, to the actions of Agents. The set of agents will be the tutor and other learners in a collaborative learning system. So we will attempt to model the learner's emotional response after an action made by one of these agents (tutor and other learners). For future studies we will concentrate also on modeling the emotional reaction of the tutor following an action from the learner.

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