Emotion Generation Model for Tutoring Agents

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교육용 에이전트를 위한 감성 생성 모델

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요약

메타포는 인터페이스 구현의 근간을 이루는 방법론으로 인터페이스의 발전과정은 바로 이 메타포의 패러다임적 진화과정이라고 할 수 있다. 지능형 에이전트는 데스크탑 메타포의 발전된 형태로 인터페이스 설계에 새로운 패러다임으로 등장하고 있다. 무엇보다도 감성적 커뮤니케이션의 필요성이 중대됨에 따라 감성 에이전트에 대하여 다양한 분야와 관점에서 심도있는 연구가 진행되고 있다. 본고에서는 인간의 감성을 교육용 에이전트에 적용할 수 있는 인간의 감성 생성 모델을 제시하고자 한다.

The interface metaphor has been evolved gradually from desktop to agent-oriented paradigm. Multimedia contents could be simply recognized as the multimodal communicational interface. In this respect, the emotional agents are actively focused as the research topics to test the possibility for realizing anthropomorphized and sympathetic interfaces. In this paper, the emotion generation model for tutoring agents is suggested.

1. Introduction

Information explosion and widespread availability of computing environments for public require the highly effective and user-friendly interface for accessing and extracting valuable information. Software agent seems to promise the advent of new paradigm for intelligent and emotional communication channels for this seemingly uneasy task.

Especially emotional software agent is actively focused on its implementational correlate, life-like character, usually called cyber-character or avatar, and is ready to replace traditional desktop metaphor with highly interactive human-like and emotion-oriented animated metaphor. As multimedia contents are increasingly reconfigured and upgraded for the Web environments, and general publics are accustomed to and becoming active supporters for cyber-communication, the highly sophisticated models for Web-based intelligent tutoring/learning are developed with unusual enthusiasm [1][3][6][10][11][13][19]. Tutoring agents are entities whose ultimate purpose is to communicate with the student in order to efficiently fulfil their respective tutoring function, as part of the pedagogical mission of the system. The fundamental reason for introducing agents as tutoring knowledge elements is their capabilities of communication and interaction. Hence, the tutoring agents with animated and emotional presentation are actively supported by many researchers[8][17]. These approaches add expressive power to a system's presentation skills and engage students without distracting them from the learning experience.

In this paper, the attributes and structures of emotional agents for tutoring environment are introduced.

2. Computational model for emotion

Life-like characters, visually anthropomorphic, emotional agents, play an important roles in instructional multimedia contents by offering user-friendly, user-oriented, and highly learning-motivating interactions[8][9]. Emotional agents are recently exploited based on the concept of believability[4][5][18]. The believability conceptually includes the entities like personality, emotion, self-motivation, social relationships, and illusion of life[19][18]. The structure of emotional agents comprise of the domain knowledge representation, instructional strategies, maintenance of consistent instructional dialog, and user-interface module which recognizes input stimuli and affects environments[12]. The computational model for emotion should provide the machinery necessary to account for affect and emotion. Most of researches related to this area are affected by cognitive psychology[2][6]. The modeling structure suggested in this paper is mainly based on the work from Otorny and his colleague[2]. Many emotion theorists have argued that cognitive appraisal is central to emotion. One of the most salient aspects of the experience of emotions is that they vary a great deal in intensity both within and between people. This means that a theory of emotion must address the question of what determines intensity. The intensity of emotions is influenced by a number of variables, all of which are present in the construal of the situation that gives rise to the emotion in the first place. Thus, in order to address the question of intensity, we first need to consider the mechanism whereby emotion-inducing stimuli are appraised.

3. Proposed Model

Because of lifelike tutoring agents' abilities to combine sophisticated communicative functionalities with engaging and emotional personae, they can take advantage of humans' inherent propensities to anthropomorphize software and play a central role in students' problem-solving activities[14]. In this section the proposed model is described. The model consists of three major processes: the user model, the emotional process and the agent's cognitive process. The agent first perceives certain events from the environment. These events are then passed to both the emotional process and the user model. The emotional process will take the perceived event from the cognitive process; in addition, it will use some of the user model outcomes, including expectations, and event-goal associations, to produce a behavior. In this context, the behavior can be an avatar-related movements in cyber-tutoring space or simply the emotional facial presentation of avatar with the cautiously planned learning strategies. However, several main modules are detailed in this section.

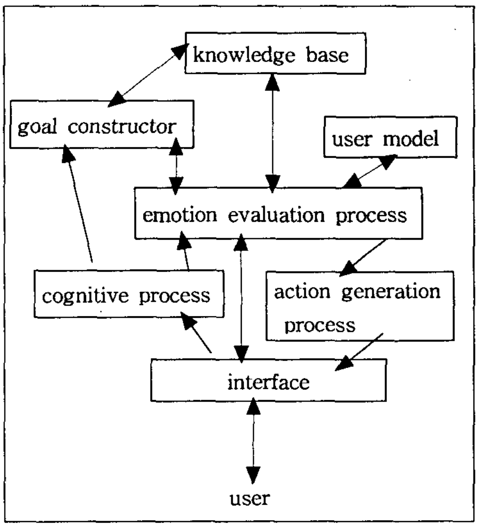


Fig.1 the proposed emotion generation model (the directions of arrows represents the events/data flows).

Emotion evaluation process

The perceived event taken from the cognitive process is first evaluated. The evaluation process consists of two sequential steps. Firstly, the user model determines which goals are affected by the event and the degree of impact that the event holds on these goals. Secondly, it proceeds to get a desirability level of the event according to the measure calculated by the first step and the importance of the goals involved. The event evaluation process depends on two major criteria; the importance of the goals affected by the event and the degree by which the event affects these goals. The desirability measure, once calculated, will be passed to next phase to further determine the emotional state of the agent. An emotion or a mixture of emotions will be triggered using the event desirability measure. The mixture will be filtered to produce an emotional state. In essence, the emotional state will be a list of emotions that apply at a specific time given a certain situation. The emotional state is passed to the behavior selection phase. Though this phase, a behavior is chosen according to the situation assessment and the emotional state. The emotional state will then be decayed and fed back to the system to the next iteration.

Goal Constructor

Most of the things that people do are motivated. People rarely engage in random actions devoid of goals and purposes. In some sense, therefore, people must have a structure of goals, interests, and beliefs that underlie their behavior. In tutoring environment, goals are described by students in terms of abstract operations they would like to see play out in the simulated world. After the goal has been completely specified, high-level goals are decomposed to create the goal-space to be usually shaped as tree structure whose leaves are action specification for the agent to perform. This module actively interacts with knowledge base and user model which supports and reflects user's learning process.

A crucial aspect of the representation of goal structure is that the representation is constantly changing as old goals are realized or abandoned and as new ones are introduced. Such changes are not limited just the addition and deletion of nodes or branches from the structure, rather, the entire configuration can change. In our efforts to build computer models of processes of this kind, we associate subjective transition probabilities with all intergoals links(more about goals, refer to [2].

The goal model suggested above might be utilized to set up computationally tractable algorithms to help us to evaluate, modify, and improve the account of computational model. That is, we need a system of rules and representations about the elicitation of emotions.

emotion	rule
joy	occurrence of a desirable event
sad	occurrence of undesirable event
disappointment	occurrence of a disconformed desirable event
relief	occurrence of a disconformed undesirable event
hope	occurrence of a unconformed desirable event
fear	occurrence of a unconformed undesirable event
pride	action done by the agent and is approved by standards
shame	action done by the agent and is disapproved by standards
reproach	action done by the other and is not approved by the agents standards
admiration	action done by the other and is approved by the agents standards
anger	complex emotion-> sad + reproach
gratitude	complex emotion->joy + admiration
gratification	complex emotion->joy + pride
remorse	complex emotion->sad + shame

Table 1. the rules to determine the emotion types.

Event appraisals

Once a desirability degree is set for an event, some rules can be fired to determine the emotional state given an expectation and a desirability measure of the perceived event. The expectation value is taken from the user model. A variation of Ortony's model[2][15] is used to define the rules used. These rules are documented in Table 1. To apply the rules shown in the table, we need a few more components. These components are summerized as follows:
(1) the desirability measure of the event, which is taken from the event evaluation process, (2) standards and event judgement, which are taken from the learning process, (3) expectation of events to occur, which are also taken from the learning process. The formula calculating the intensity of emotions[7] are illustrated in Table 2. The table shows the method by which intensities are calculated for various emotions given an expectation value and an event desirability measure.

emotion	intensity
joy	$(1.7*\text{expectation}^{0.5})+(-0.7*\text{desiability})$
sad	$(2*\text{expectation}^{2})-\text{desiability}$
disappoint-ment	hope*desirability
relief	fear*desirability
hope	$(1.7*\text{expectation}^{0.5})+(-0.7*\text{desiability})$
fear	$(2*\text{expectation}^{2})-\text{desiability}$
pride	value(event(x), standards)
shame	value(event(x), standards)
reproach	value(event(x), standards)
admiration	value(event(x), standards)

Table 4. the formula for calculating intensities of emotions

User model and learning algorithms

The agent will need to know what event to expect, how much to expect it and how bad or good it is. As explained earlier, the identification of emotions and emotional intensity heavily rely on expectations. Furthermore, events are normally measured by their impact on a set of goals. It is often the case that a given event does not have any impact on any specific goal directly, but some sequence of events may eventually have an impact on some goals. Thus identifying the link between an event and the corresponding goals was noted to be a very complex task to accomplish. The agent can potentially learn this by using a reinforcement learning algorithms, namely the Q-learning algorithm[16]. It is often the case that an agent does not know the consequences of a given action until a complete sequence of actions is finished. The agent, therefore, faces the problem of temporal credit assignment, which is defined as determining which of the actions in its sequence are responsible for producing the eventual rewards. To illustrate the solution that reinforcement learning offers to this problem, we will look at reinforcement learning in more detail. The agent represents the hypothesis or the problem space using a table of Q-values in which each entry corresponds to a state-action pair. The table can be initially filled with default vaules. The agent will begin from a state s. He will take an action, a, which takes him to a new state s'. The agent may obtain a reward r for his action. If it receives a reward it updates the table above using the following formula:

$$Q(s,a) \leftarrow r + \gamma \max_{a'} Q(s', a'),$$

where r is the immediate reward, γ is a discount factor, s' is the new state, and a' is an action from the new state s'. Thus the Q value of the previous state-action pair depends on the Q value of the new-state action pair. Since the agent is interacting with the user, the agent will have to learn about the user's patterns of actions. The agent's mind may not handle more than a length of 7 ± 2 consecutive action comparisons[15].

4. Simulation and conclusion

The implementation of emotion generation model proposed above in real situation is under way. Here, very simple simulation model is suggested and tested. A model for representing contours in an image in a form that allows interaction with higher level processes has been proposed by Kass et al.. This popular model is represented by a vector, $v(s)=(x(s), y(s))$ having arc length, s, as parameter. They define an energy functional for the contour by:

$$E_{snake} = \int_0^1 E_i(v(s)) + E_{im}(v(s)) + E_{con}(v(s))\,ds$$

where E_i represents the internal energy of the contour due to bending or discontinuities, E_{im} is the image forces, and E_{con} is the external constraints. In this simulation, the first-order term will have larger values where there is a gap between goals. The desirability of an event may be lower when the distance between the focal goals and the desirable target goals. The second-order continuity term will be smaller where the expectation value of focal goal is small. The derivative terms of the equation above can be approximated by finite differences. Also greedy algorithm is presented which allows a contour with controlled first and second order continuity to converge on an area of high image energy. At first, the Gaussian virtual goal-space is generated to reflect the final focal goal located to the minimum energy point as shown Figure 2.

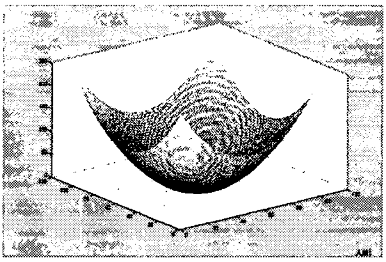


Fig.2 the virtual goal space

The desirability measure is simulated as the $d-|v_i-v_{i-1}|$, where d is the averaged distance between the adjacent two goals. Thus events having distance near the average will have the minimum value. Average value could be considered the current focal goal to the final focal goal at given time t.

At the end of each iteration a new value of d is computed, which surely converges to the nearest focal goals. The convergence process could be considered as the decay functions of emotions, which are rarely exploited in formal way[15].

The second term is used as the expectation values, since the formulation of the curvature term causes the neighboring goals in goal sequence to be relatively closely spaced, $|v_{i-1}-2v_i+v_{i+1}|^2$ give a reasonable and quick estimate of curvature.

The following is the pseudo-code for Greedy algorithm for this simulation settings.

```
n= number of goals generated by an event
m=size of neighborhood of a goal
Index arithmatic is modulo n
Initialize αi,βi, and γi to 1 for all i.
```

```
do /*loop to move events to new event locations */
 for i=0 to n /* process point 0 first and last */
   Emin=BIG
   for j=0 to m-1
     Ej= αi Ejdesirability+βi Ejexpectation
      if Ej < Emin then
        Emin=Ej
        jmin=j
        Move event vi to event location jmin
        if jmin not current event, ptsmoved++
          /* count events moved */
        Generate emotions
until ptsmoved < threshold
```

Figure 2 shows the randomly generated goal list of an event. Figure 3 shows the desirability and expectation measures to be used to calculate the simulated emotions.

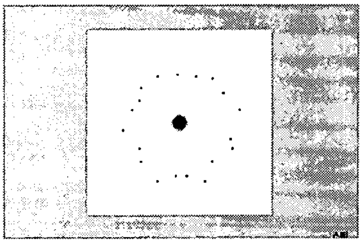
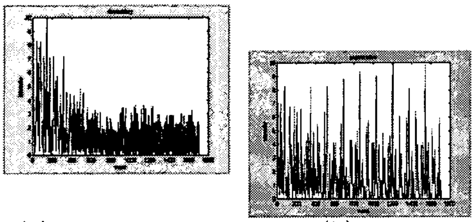
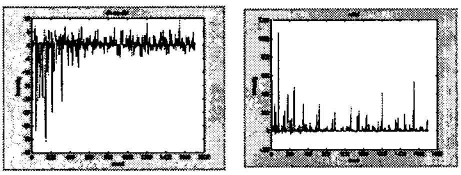


Fig.2 the goal list of an event generated randomly upon the goal space.



(a) (b)

Fig.3 (a) the desirability measured, (b) the expectation values



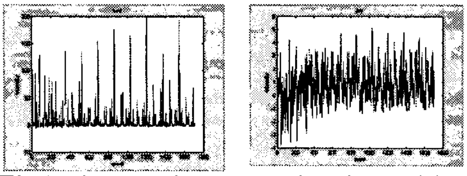


Fig4. the resultant emotion intensities related with joy, sad, disappointment, and relief.

This simulation has several issues to solve. First, the parameters used here are not verified formally. Secondly, the goal-space is oversimplified to reflect the real situation. Thirdly, the user model should be very complex compared with this simulation model. However, what I contribute here is the suggestion of emotion generation, decay model and the exposure of the computational model of emotion.

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