Designing an Action Selection Engine for Behavioral Animation of Intelligent Virtual Agents

F. Luengo[1,2] and A. Iglesias[2,3,⋆]

[1] Department of Computer Science, University of Zulia,
Post Office Box #527, Maracaibo, Venezuela
fluengo@cantv.net

[2] Department of Applied Mathematics and Computational Sciences,
University of Cantabria, Avda. de los Castros, s/n, E-39005, Santander, Spain

[3] Laboratory of Advanced Research, Building B, Room #1025,
University of Tsukuba, Kaede dori, Third Cluster of Colleges, Tsukuba, Japan
iglesias@unican.es
http://personales.unican.es/iglesias

Abstract. This paper presents a new action selection scheme for behavioral animation in computer graphics. This scheme provides a powerful mechanism for the determination of the sequence of actions to be performed by the virtual agents emulating real world's life. In particular, the present contribution focuses on the description of the system architecture and some implementation issues. Then, the performance of our approach is analyzed by means of a simple yet illustrative example. Finally, some advantages of our scheme and comparison wih previous approaches are also briefly discussed.

1 Introduction

The issue of *action selection* has been largely analyzed in the framework of ethology and cognitive sciences [2, 22, 23], psychology [14] and robotics [1, 15]. More recently, it has also become an interesting challenge for behavioral simulation in computer graphics [4, 5, 6, 20, 21]. Roughly speaking, it can be established as follows: *at each moment of time, given a set of feasible goals to be performed, we want to choose the most appropriate one based on the agent's internal and external conditions*. In other words, the central problem to deal with is the determination of the sequence of actions to be performed by the virtual agents as a function of internal and/or external factors. Of course, this determination is expected to be *realistic*, since we are going to use virtual agents to simulate human beings with a certain level of realism.

From the previous definition, it becomes clear that the construction of appropriate schemes for action selection is a key component in behavioral animation

⋆ Corresponding author.

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of virtual characters. Because of that, a number of different proposals have been described in the literature (see, for instance, [1, 2, 5, 6, 7, 12, 13, 16, 17, 18, 20, 21] and references therein).

In this paper, a new framework for action selection is presented. We point out here that this action selection system is actually a module of a whole behavioral animation system already described in previous references [8, 11]. The reader is also referred to [9] and [10] for more details about such a behavioral system.

The structure of this paper is as follows: Section 2 describes the architecture of this new approach and its simulation flow as well as some implementation issues. The performance of this new scheme is analyzed in Section 3 by means of a simple yet illustrative example. Finally, some advantages of our scheme and comparison wih previous approaches are briefly discussed in Section 4. Conclusions and further remarks close the paper.

2 The Action Selection System

This section describes the action selection system introduced in this paper. Firstly, we focus on the description of the system architecture. Then, some implementation details are also given. Finally, the simulation flow is briefly analyzed.

2.1 System Architecture

The architecture of the action selection system described in this paper is displayed in Figure 1. It consists of a *goal database* and three different modules (the emotional analyzer, the intention planning and the action planning) intended to perform specific tasks as described below.

The first component of our system is a database that stores a list of arrays (associated with each of the available goals at each time) having the structure:

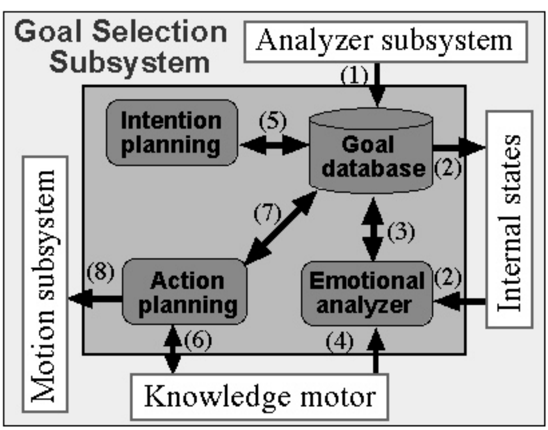

Fig. 1. Architecture of the goal selection system

Table 1. Variables associated with each goal stored into the database: variable names (left) and their meaning (right)

Variable		Meaning
`goalid`	-	goal identification code (see Section 3 for a list of feasible goals for the example described in this paper)
`feasr`	-	goal's feasibility rate
`priority`	-	goal's priority (determined by the intention planning)
`wishr`	-	wish rate (determined by the emotional analyzer)
`t`	-	time at which the goal is selected
`successr`	-	goal's success rate

```
[goalid, feasr,priority, wishr, t, successr]
```

where the meaning of each variable is indicated in Table 1. On the other hand, an additional array is stored only for the current goal in progress: `[tsel,tatt]`, the components being the time at which the goal has been selected and attained, respectively.

The *emotional analyzer* is the module responsible to update the wish rate of a goal (regardless its feasibility). Such a rate takes values on the interval $[0, 100]$ according to the mathematical functions describing the agent's internal states[4]. Those functions involve the internal state variables described in Section 3 as well as two parameters:

(1) the *dynamic rate*, D, which expresses the agent's predilection for dynamical activities (such as walk or run) over the intellectual ones and
(2) a temporal parameter Ω_k, defined as:

$$\Omega_k = \alpha_k \, \delta_k \, \frac{t - t_m}{t - t_k} \tag{1}$$

where Θ is the set of all possible goals, $t_m = \min\limits_{j \in \Theta, j \neq k} t_j$, where t_j is the simulation step at which the j-th goal was selected for the last time and k the current goal, t is the current time, $\delta_k \in \{1, 1.2\}$ is a parameter that accounts for the goal's success (successful goals exhibit higher wish rate than those unsuccessful), and $\alpha_k \in [0, 2]$ is a parameter used to promote some particular goals with respect to others, depending on the agent's personality. Note that the role of Ω_k is to increase the wish rate of the oldest goals in the priority list (i.e. the older a goal, the higher its wish). This simple procedure assures that, for a sufficiently long span, all possible goals will be finally selected. Note also that this condition can be easily skipped by simply omitting this factor in the equations of the internal states.

[4] The mathematical description of the internal state functions corresponding to the example described in this paper is not included here because of limitations of space. For the definition of those functions for a different example, the interested reader is referred to [10].

The *intention planning* module determines the priority of each goal. To this aim, it uses information such as the factibility and wish rate. From this point of view, it is rather similar to the "intention generator" of [20] except by the fact that decision for that system is exclusively based on rules. Our intention planning module also comprises a buffer to store temporarily those goals interrupted for a while, so that the agent exhibits a certain "persistence of goals". This feature is specially valuable to prevent agents from the oscillatory behavior appearing when the current goal changes continuously.

The last module is the *action planning*, a based-on-rules expert system that gets information from the environment (via the knowledge motor described in [8]), determines the sequence of actions to be carried out in order to achieve a particular goal and updates the goal's status accordingly. These actions are transferred to the motion subsystem to be converted into graphical instructions subsequently sent to the graphics pipeline.

2.2 Implementation Issues

Concerning the implementation details, the action selection module presented here has been developed in Visual C++ v6.0 on a PC platform with Pentium IV processor and 256 MB. of RAM. The graphical output has been implemented on Open GL with GLUT and subsequently compiled in Visual C++.

It is interesting to remark that our decomposition of the goal selection module into four subsystems as described in Section 2.1 is very useful from the programmers' viewpoint: on one hand, maintenance, debugging and updating of the system components are much easier and simpler. On the other hand, any function can be modified by simply rewritting some code lines of the particular subsystem at which this function is implemented.

2.3 Simulation Flow

Figure 1 depictes the simulation flow of the goal selection system described above. Firstly, the analyzer subsystem updates the factibility, which is stored into the goal database (step (1) of that figure). Then, the emotional analyzer gets information about:

- the internal states from the internal states subsystem (2),
- the time at which each goal is selected/attained from the goal database (3) and
- relevant parameters from the knowledge motor (4).

This information is used by the emotional analyzer to update the goals' wish rate at the goal database. The factibility and wish rates are sent to the intention planning module (5) to determine the priority of each goal, which is subsequently updated at the goal database. Then, the current goal is sent to the action planning module. It takes additional information on the environment from the knowledge motor (6) in order to run the set of actions associated with such a goal. This will modify the agent's status within the virtual 3D world (and, hence, the knowledge motor as well). Information about the actions is sent to the goal database (7) to update the goal's status (failed, candidate, in progress). Finally, those actions are sent to the motion subsystem (8) to be converted into graphical instructions.

3 An Illustrative Example

In this section, the performance of the goal selection scheme is analyzed by means of a very simple yet illustrative example. We remark that this example is considered here for illustrative purposes only. In fact, more complex scenarios can be easily generated from our system.

The scene consists of a shopping center at which the virtual agents can perform a number of different actions, such as eat, drink, play videogames, sit down to rest and, of course, do shopping. The environment also comprises different static (such as trees, tables, shops) and smart objects (such as benches, videogame machines, drink machines). Therefore, it is a convenient place for a wide range of potential agent-object and agent-agent interactions. To this aim, we consider four virtual agents, three kids and a woman.

Figure 2 shows the temporal evolution of the internal states (top) and the goals' wishes (bottom) for one of the kids. Similar graphics can be obtained for the other agents (they are not included here because of limitations of space). The picture on the top displays the temporal evolution of the five internal state functions (valued onto the interval $[0, 100]$) considered in this paper, namely, `energy`, `shyness`, `anxiety`, `hunger` and `thirsty`. On the bottom, the wish rate (also valued onto the interval $[0, 100]$) of the feasible goals (`have a rest`, `eat something`, `drink water`, `take a walk` and `play videogame`) is depicted.

In the example described in this paper, the following initial values for the agent's internal states and parameters have been chosen: `energy=100`, `shyness=0`, `anxiety=0`, `hunger=0` and `thirsty=0`. Therefore, the kid is very sociable and dynamic and likes activity very much, while being neither hunger, nor anxious nor thirsty at all. Both pictures in Figure 2 are labelled with eight numbers indicating the different simulation's milestones (the associated animation screenshots for those time units are displayed in Figure 3):

(1) At the initial step, the three kids go to play with the videogame machines, while the woman moves towards the eating area (indicate by the tables in the scene). Note that the internal state with the highest value for the agent analyzed in this work is the energy, so the agent is going to perform some kind of dynamic activity, such as to play.

(2) The kid keeps playing (and their energy level going down) until his/her satisfaction reaches the maximum value. At that time, the anxiety increases, and the agent'wish turns into performing a different activity. However, the goal `play videogame` is still that with the highest wish rate, so this goal will be in progress for a while.

(3) At this simulation step, the anxiety reaches a local maximum again, meaning that the kid is getting bored about playing videogames. Simultaneously, the

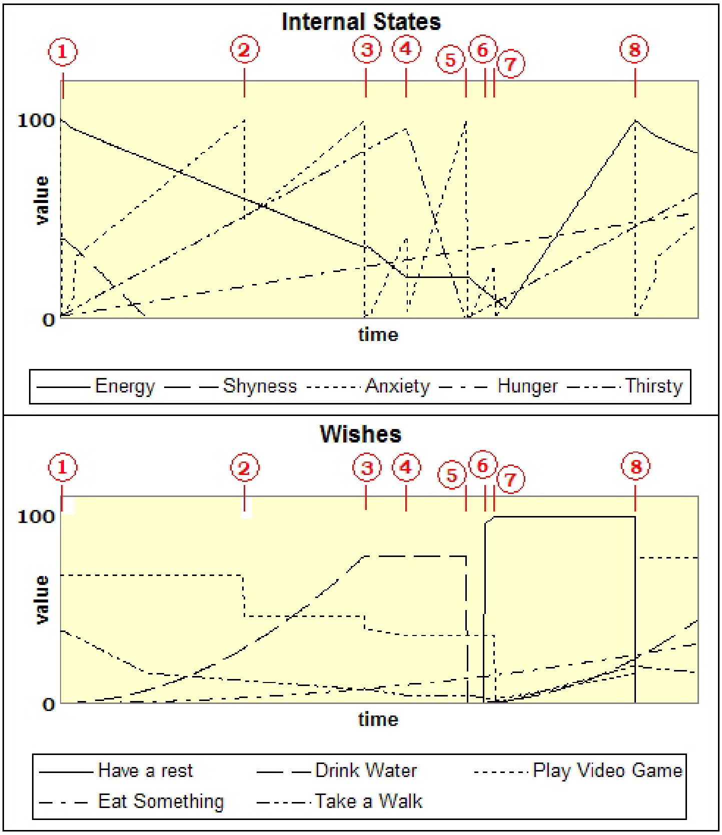

Fig. 2. Temporal evolution of the internal states (top) and available goals' wishes (bottom) for the example in this paper

goal with the highest value is `drink water`, so the agent stops playing and starts to look for a drink machine.

(4) At this time, the kid gets the drink machine and starts to drink. Consequently, the internal state function `thirsty` decreases as the agent drinks until the status of this goal becomes *goal attained*.

(5) Once this goal is satisfied, the goal `play videogames` is the new current goal. So, the kid comes back towards the videogame machines.

(6) However, the energy level is very low, so the goal `play videogames` is interrupted, and the kid looks for a bench to sit down and have a rest.

(7) Once seated, the energy level turns up and the goal `have a rest` does not apply anymore.

(8) Since the previous goal `play videogames` is still in progress, the agent comes back to it, and plays again.

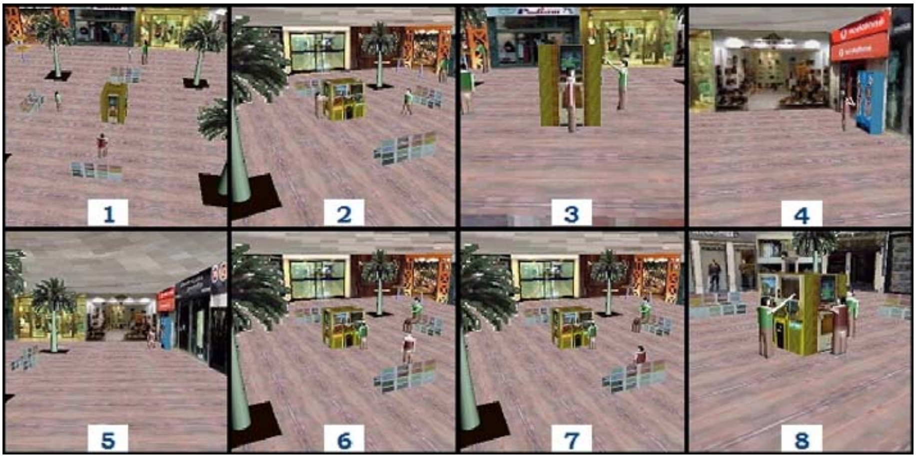

Fig. 3. Screenshots of the shopping center example

The results show the excellent performance of the present scheme. In particular, the six criteria used in [18] to validate a motivational model for action selection are also fulfilled here:

– the motivations are taken into account (criterion 1) via the goal's wish function. Additionally, "the persistence of motivations" is also included into the system. Note, for instance, that at step (5) of our example the goal `play videogames` exhibits the highest value (and hence, it is the current goal). However, it is interrupted by the goal `have a rest` as the agent is too much tired to keep playing at that time. After a while, the agent's energy level is high enough to return playing, and the former goal is subsequently recovered at step (8).
– In addition, the environment information (criterion 2) is provided by the knowledge motor and used to determine the goal's feasibility and perform the actions in sequence for the current goal accordingly (criterion 4).
– On the other hand, the opportunistic behavior can interrupt the current goal (criterion 5). The compromise behavior (to choose the action which satisfies the greatest number of motivations) is also considered here via the intention planning subsystem (criterion 6).
– Finally, criterion 3 (to prefer motivated actions over locomotion actions) is also considered here. In fact, the most important goal for the kids in our example is to `play videogames`, as it is the most dynamic activity available in the shopping center environment. However, we do not expect this criterion to be true everytime-everyone. Back to front, our system allows a richer variety of behaviors ranging from dynamic to softer goals. Such a choice is carried out by using the dynamic parameter of Eq. (1), as described above.

4 Comparison with Previous Approaches

Some interesting features of the present action selection system exhibit certain similarities with others from previous schemes. In particular, the architecture of our goal selection system represents a substantial improvement of that in [6], in which the characters' behavior mechanism is based on compact table-based descriptions and flexible scripts. However, the proposal in [6] is much simpler since it is restricted to a particular case and it is environment and input-device dependent, while ours is extremely flexible: agents can adapt to any environment without modifying the undelying structure. In fact, the process only requires the simple addition and/or modification of the internal states and parameters.

On the other hand, the short-term memory and computer redundancy avoidance via cascading and reusing of [3] are actually applied in our approach, although not exactly in the same way (see [10] for more details). Another advantages are the inclusion of personality (described in terms of different parameter values and functions) and uncertainty (performed through some probability terms, so that different agent parameters lead to a drastically different reactions). Another interesting feature of our system is the use of different Artificial Intelligence techniques for autonomous reasoning. They will be reported in detail in a future publication somewehere else.

5 Conclusions and Future Work

In this paper, a new action selection scheme for behavioral animation of virtual agents is introduced. The paper describes its design and implementation issues as well as its simulation flow. The performance of this approach has been shown by means of an illustrative example. Finally, comparison with previous (similar) approaches is briefly discussed.

Despite of the encouranging results, this is just one step to reproduce realistically the huge range of complex human behaviors and there is a long way ahead. In particular, further research is still needed in order to describe many human behaviors in mathematical terms: some functions are to be improved, others have to be defined yet. On the other hand, we are interested to describe human emotions and how they do influence the decision process [19]. Subsequent versions of this model will include many additional modifications and improvements. However, we do not expect to modify the current design and implementation of our action selection system significantly.

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