Building an Intelligent Behavior Avatar in the Virtual World

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Abstract

As the prevailing of the avatar application, it is possible for a computer to behave like a man in a virtual environment. Due to the avatar can not think and behave like a man, the decision-making is the problem to design an intelligent avatar. In this paper, an intelligent behavior avatar is proposed to solve personalized problems, and improve the traditional avatars to make decisions. The IBA model is designed by Bayesian networks and decision theory. It not only imitates user's behavior style to live in the virtual world, but also adjusts itself to make proper strategies in varied environment by using the proposed reasoning and self-learning mechanisms. The performance penalties caused by the interaction between avatars and objects in the virtual world can be solved by the proposed smart object. From the experiment results, it shows that the efficiency of the interaction within IBAs can be obtained by using the proposed smart object.

Keywords: Intelligent behavior avatar, Bayesian networks, decision theory, virtual environment

1. Introduction

The intelligent agents have been used in various fields in the past years. Computers can be used to replace the human behavior on the common routine works. However, in the practical situations, the computers can not think by themselves, it is a big problem for the computers to make proper decisions.

The traditional behavior avatar (TBA) usually makes decisions by a static knowledge-based system [1]. In this way, the behaviors of the agent are too regular to be like a real human being. The decision making style can not be changed according to the personal characteristics. An intelligent behavior avatar (IBA) model is proposed to solve this problem. This model is based on the Bayesian networks and combined with the concepts of the decision theory [1]. Based on the proposed reasoning and self-learning mechanisms, the IBA can imitate human's behaviors. IBA also has the intelligent thinking flow to make appropriate decisions in the changed environment.

In this paper, section 2 is the related works. Section 3 is the proposed system architecture. Section 4 is the implementations and the comparisons for different behavioral models. Finally, the section 5 is the conclusions and future works.

2. Related Works

The Bayesian network (BN) [2] is a directed acyclic graph that is constructed by a set of variables coupled with a set of directed edges between variables. The BN is very successful in reasoning between variables via conditional probabilities. A typical BN is shown in Fig. 2.1, and it consists of the following elements:

- A set of variables and directed edges between variables.
- Each set contains a finite set of mutually exclusive states.
- The variables coupled with the directed edges are used to construct a directed acyclic graph (DAG).
- Each node (A) with parents (B1,…,Bn) has a conditional probability P(A|B1,…,Bn) .

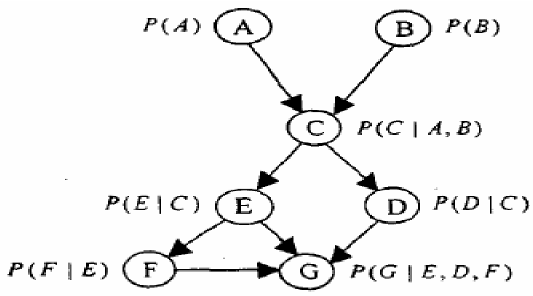

Fig. 2.1 An example of BN

A BN provides an effective way to deal with uncertainty and complexity [3][4]. It can describe and predict the probability of the given target, therefore, it is a good tool for real world analysis and decisions makings.

To make such choices, an agent should first have preferences between the different possible outcomes of the various plans. The utility theory is used to represent and reason with preferences, and the decision theory is used to be the principle of decision making [5]. The basic idea of decision theory is that an agent is rational if and only if it chooses the action that is the highest expected value, or the average value over all possible outcomes of the action. Probabilities and utilities are combined in the evaluation of an action by weighting the utility of a particular outcome and the probability that it occurs.

3. System Architecture

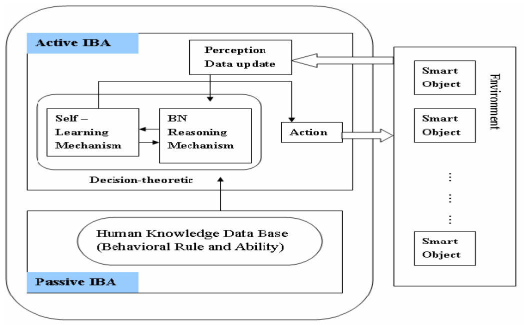

Fig. 3.1 The architecture of our system

As shown in Fig 3.1, there are two main modules in our system, the IBA and the virtual environment. The IBA is a basic element to detect the dynamic changes in the environment. While a user comes into the virtual world, an IBA is allocated to each of them. The virtual environment consists of a lot of smart objects to be acted with IBA.

3.1 Smart Object

In the virtual world, the IBA cannot know about the environment while exploring in the world space. The smart object (SO) [6] is built to help the IBA to get the information from the space conveniently and quickly. The SO is triggered by IBA and then provides a behavior list (Fig. 3.2) for IBAs to select actions. After determining the favorite actions of the IBA, it will be executed on the SO.

Smart Object Name	Attribute	Interactions	Description
Virtual Human	Hp=40 Experience=20 Attack=10	Talk	Add experience value
		Attack	Lose hp and add experience value
		Business	Exchange any thing

Fig. 3.2 The behavior list of SO

3.1.1 Action Table

There are two defects will be revealed while the inner communications hits to the bottleneck of the interaction limits in the system. For users, they waste much time to read the behavior list; and for IBAs, they increase the complexities of calculations. Therefore, we use the action table (AT) to avoid these two problems as possible.

The AT is similar to a catch table. Unlike the behavior list which to record every action for the IBA; it just stores some actions which are the most selected actions by IBA. Thus, it reduces the numbers of interactions, and increases the efficiency of the system. Whether the IBA determines the action from behavior list or AT, it will request SO to update the AT by the statistical data for each action in the previous experiment. When user can’t find the preferred actions in AT, it is necessary to trace back to load the complete behavior list in order to provide users to choose other actions.

3.1.2 Relationship between SO and IBA

The relationship between SO and IBA is described in the following figure:

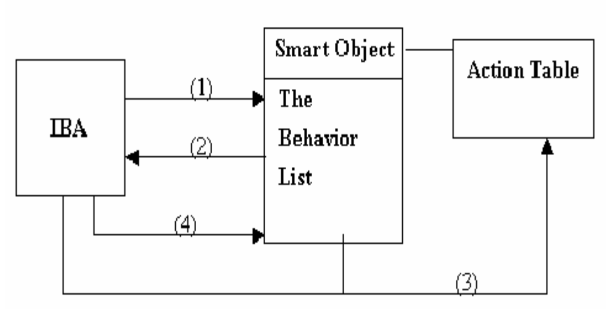

Fig. 3.3 The interaction flowchart of SO and IBA

There are four kinds of interactions in the system:

(1) IBA triggers for SO.
(2) SO provides a list for IBA to select the action.
  i. If AT isn’t NULL then show the AT.
  ii. Else show the original behavior list of SO.
(3) SO requests for IBA to update the AT.
(4) IBA do the action which it chose to this SO.

3.2 Intelligent Behavior Avatar

The main purpose of IBA is to imitate the human being’s behaviors, and to make the proper, yet more intelligent decisions. Moreover, the IBA has it capabilities to adapt itself in the changed environment. The typical IBA has two types: passive and active IBA, and will be introduced in the following section.

3.2.1 Passive IBA

The definition of the passive IBA is that it is controlled by human manually. It records every action that human did in the virtual world. The record history includes the ability of IBA, the outside environment, and the action, and those data will be used by the active IBA.

3.2.2 Active IBA

Unlike the passive IBA, the active IBA means it is not controlled by human beings. The functions of active IBA can be divided into three parts: the BN decision model, the reasoning and the self-learning mechanism.

The BN decision model is based on the relation graph of the BN. Because we want to simulate a virtual world which is like a world in Role Playing Game (RPG), we need to construct a relationship graph which saves the important features in the world, such as abilities of IBA, and outer changed effects in the environment. The decided action will also influence the player type (Fig. 3.4). There is a conditional probability table (CPT) in every node to provide the reasoning mechanism to calculate.

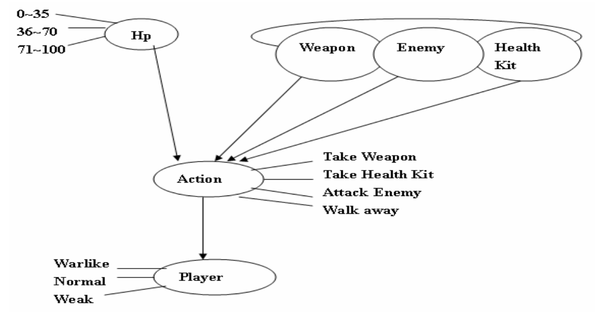

Fig. 3.4 The BN relation graph

The reasoning mechanism [7] is help us to infer which action the IBA will do next step. There are two phases to predict actions:

Observation phase: The active IBA uses the observed event (evidences) to compute each conditional probability of the evidence.

Reasoning phase: The system uses formulas to compute the uncertain event probability. Calculations of the probabilities of uncertain propositions are based on the previous research work proposed by Pearl [8].

$$P(X \mid e) \propto P(e^c \mid X)P(X \mid e^p), \qquad (3.1)$$

where P(X|e) presents final occurrence probabilities of each action, and P(ec|X) is the conditional probability of the evidence of four nodes which we describe in above. P(X|ep) is the nodes of the player. After computing P(X|e), the active IBA picks up the highest probability to be the action which the IBA will execute it on SO.

There is a starvation situation which may be caused if the active IBA always selects the highest probability action and neglects other actions with minor probabilities. Thus leads the avatar will acts in regular form, and can not modify its behavior while the environments changed. So we add the self-learning mechanism into the active IBA to solve the problem, and make it be more clever and closed to human beings. The algorithm is discussed by the following three parts:

(1) To prevent the avatar can not exist in the virtual environment: Before the avatar does the action, it will pre-determine its life value. If doing this action leads to the Health Points (HP) is less than zero (HP<0), then the active IBA will chooses another higher actions to do.

(2) To avoid actions occurring starvation: We use the concept of counting algorithm [9] to solve this problem. Giving each action a counter to count how long the action is not executed. The actions will get higher priority to be executed when the avatars stay in idling situation for a long time. If the avatar selects Action1 in this time, the value of Counter1 will not be changed, but others will add one point to accumulate the value of counters. The active IBA will select the action which the probability is the highest.

$$Utility_i = benefit_{Action_i} \cdot \alpha \qquad (3.2)$$

(3) Pre-compute benefits of every action through the equation 3.2, and give a feedback to increase the probability of the action which can gain more benefits on it, and decrease the others. The formulation of counting feedback value is listing as follows:

The feedback of the highest utility action:

$$Feedback_{Action} = (\sum_i P(Player_i \mid Action_i)\cdot \lambda_i)\times \alpha \qquad (3.3)$$

$$P(Action \mid Ability \ \& \ Environmen\ t)_{new} = P(Action \mid Ability \ \& \ Environmen\ t) + Feedback \qquad (3.4)$$

The feedbacks of others:

$$Feedback = \frac{(\sum_i P(Player_i \mid Action_i)\cdot \lambda_i)\times \alpha}{Number\ of\ no\ exexuted\ and\ possible\ actions} \qquad (3.5)$$

$$P(Action \mid Ability \ \& \ Environmen\ t)_{new} = P(Action \mid Ability \ \& \ Environmen\ t) - Feedback \qquad (3.6)$$

4. Simulation Results

We build a virtual environment to simulate our proposed architecture. There are three SOs in the system: weapon, health-kit, and enemy. As for passive IBAs, they use rule-based decision making strategy to build the real human's behaviors. For active IBAs, there are three different models in its living strategies: reasoning model, self-learning without feedback model, and self-learning model. We compare each model and demonstrate the results with life graphs in two different experiments.

In the first experience, we produce a lot of random environment parameters for the passive IBA to select an action sequence and draw a life graph. The same parameters have been used in the active IBA models.

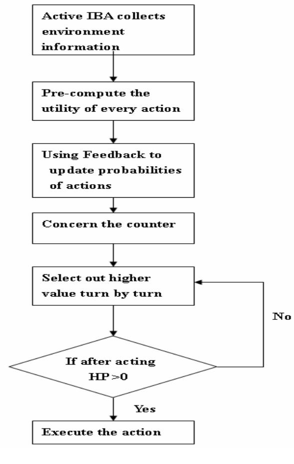

Fig 3.5 The flowchart of self-learning mechanism

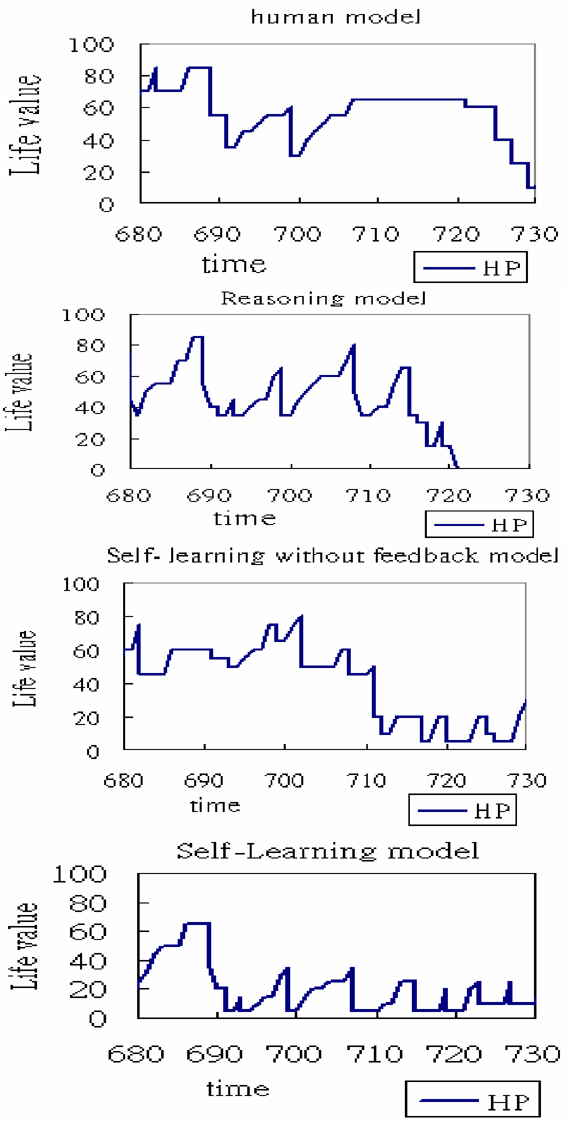

Fig. 4.1 Four models of life graph in the experiment 1

As shown in Fig. 4.1, the IBA can not be always alive in the reasoning model, but via our self-learning mechanism it can continue to survive in the world. Fig. 4.2 is the results of experiment 2. Because of the probability of the attack action is not the highest one, the IBA in the reasoning model will not choose the attack action while it is in the low life value, and hence it can be alive in the world. Comparing with the life curves of four models, the highest point appears about on 13360, and then decrease, and rise again on 13380. We can notice that the IBAs with various models have the similar behavior. The active IBA can really imitate human's behavior and has its thinking to make decisions to live in the virtual world.

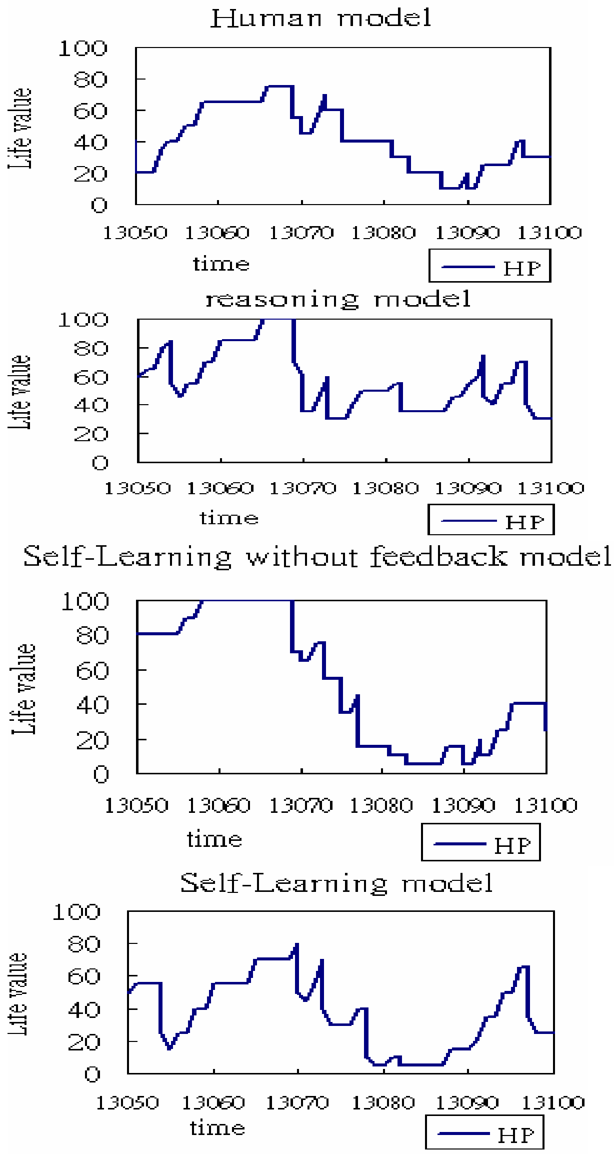

Fig. 4.2 Four models of life graph in the experiment 2

5. Conclusions

In this paper we design an IBA that can imitate human's behavior and make decision itself successfully. We use the reasoning mechanism to help the IBA achieving that replace human to make decision personally. And the self-learning mechanism let the IBA to own the ability of self determinations to select the proper action to execute. It is proved that the IBA not only imitate human's behavior but also has its own thinking by the simulation results.

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