Intelligent Virtual Agents Architecture in Unknown Environment

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Abstract

As the contemporary performing behavior in the reciprocity of virtual agents is glazed excessively and can't satisfy complex unknown environment, the research of Intelligent Virtual Agents (IVA) with active learning and local apperception must be accelerated. In this paper, we design and implement a new IVA system architecture, for which active learning and local apperceive interaction were approached. Active learning using knowledge acquisition and knowledge evolution improved the self-regulation of behavior mechanism significantly, while local apperceive interaction could sense disturbances of the simulated environment and interactively communicate with other simulated agents within perception dimension effectively. Ultimately, the experimental result provides effectiveness and practicability of the performance in our prototype IVA system.

Keywords: *Local Apperceive, Mobile Agents, Learning Algorithms*

1. Introduction

Creating socially Intelligent Virtual Agents (IVA) that can interact with person and other virtual characters in a natural way is a great challenge [1]. Those characters should have their emotional and behavior personality and make decisions with respect to their goals, as well as behave emotionally and socially during their interaction with other characters considering their past interactions [1][2].

To design and implementate of IVA system with highly immersion and natural reciprocity, it is obviously necessary and essential to comprehensive research of intelligent agents framework provided with active learning and local apperceive interaction, especially in large complex virtual training system and Decision-making Support System (DSS). In contrast, the current performance behavior in the interaction of virtual agents is glazed excessively and can't satisfy dynamic changing external environment which is also viewed as unknown environment.

Believability and efficiency of virtual agents are incomplete, which decrease the user experience. Virtual intelligent agent needs a methodology to response rapidly to the events occurred in virtual environment, and decides initiatively on how to implement the reactions, according to its own status and external situation. The research of IVA with active learning and local apperception ability and the problem of processing streaming data generated by IVA system become one of hot topics of the virtual reality and artificial intelligence.

The rest of this paper is organized as follows. Section 2 mentions the related work of IVA with active learning and local apperceive interaction. In section 3, we discuss the system architecture and modules in detail. In section 4, the paper describes how to implement the IVA system followed by the conclusion.

2. Related Work

Presently, the research and application about IVA with active learning and local apperceive interaction is still in initial exploring stage. Iglesias [3] presented a new framework for behavioral animation of virtual actors, while the framework applied several artificial intelligence techniques to build a sophisticated behavioral system so that the actors can take intelligent decisions by themselves. However, behavioral animation of virtual actors of the system cannot adapt dynamically to changing run-time environments. Stéphane Sanchez [4] presented the virtual behaviors framework used to simulate a "virtual brain" capable of generating, in real time, behaviors for virtual characters. The main originality of Virtual Behaviors is to combine usual behavioral animation techniques with a learning engine based on Learning Classifiers Systems in order to obtain actors that can learn how to adapt to their dynamic environment and how to efficiently combine known tasks in order to perform the user's tasks. However, the virtual behaviors framework is unable to express the blurred status of virtual world. BI Jing [5] presented a cooperative motion strategy of multi-NPC (Non-Player Character) for online games, based on analysis of behavior and feature of NPC. It described local individual threat and overall community threat of NPC by artificial potential field, while based on threat and own state Information, it can compute the next best position of NPC by particle swarm optimization (PSO). HUANG Xiang-yang [6] presented a computational model of novel situation calculus-based active NPC. To improve inherent uncertainty of behavior and practicability of cognitive model, it used epistemic fluent K in situation calculus to describe the uncertainty of behavior result, and enabled cognitive model to transform Practical world model freely using perception model. However, the extended situation calculus based on cognition, thinking and action of NPC was only used in special virtual environment.

In recent years, the domestic and international study on the agent-based modeling of IVA touched mainly the next three problems:

(1) On affective computing. [4, 7, 11] discuss the modeling method of affective computing and simulate the characteristic well fitting for basic human mood instability, which improves the believability of virtual agents markedly. (2) On apperceive interaction. Apperceive interaction system modeling, including [6, 8], makes agents simulation reasonable and vivid by the design of Perception weight parsers. (3) On behavior control. Behavior modeling and motion control technology are investigated, in [8, 9], and complex motion control of virtual agents is achieved using behavior control modeling and behavior selective mechanism.

In current research on virtual agent, IVA has not realized the architecture with organic combination of active learning and local apperceive interaction function in an undetectable virtual environment, which reduces the ability of NPC intelligent decision-making and limits the emerge of Community, intelligence and believability of invirtual agents. The comprehensive virtual intelligent agents involved in active learning, emotional interaction and dynamic apperceive function has become a new research tendency.

To solve the shortcomings in previous studies, we design and implement a new IVA system architecture. Active learning using knowledge acquisition and knowledge evolution module based on production rules, improves the ability to adapt to dynamic complex virtual environment. Intelligent agent has the capability of local apperceive and initiatively receive external information for self-regulation, with the purpose of improving the ability of adapting to the complex and ever-changing environment.

3. IVA Framework

Based on previous research results and literature material, we design an interactive system architecture which is based on active learning and local apperception in the complex virtual environment, and which is reference to the basis action and perception ability of the human in real word.

The IVA system consists of IVA User Client, Virtual World Manager and IVA Framework. The separation of Virtual World Manager and IVA Framework are necessary, with the purpose of simplified and meticulous division modules are implemented by using component design. Virtual World Manager represents a virtual environment inside which the entire agent system's activity takes place. And it realizes the attributes and states manager, including the traffic light time and weather change manager in virtual world.

IVA framework is the core part in this system. Consequently, the discussion of this paper mainly focused on the four modules shown in the figure 1. Before we launch into the model of active learning and local apperceive interaction, the key features of agent should be given. Intention, randomness and geometry are the three key features in our system.

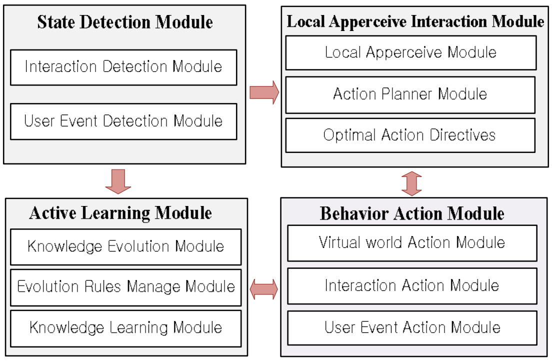

Figure 1 Main Components of IVA Framework

3.1 Local Apperceive Interaction Module

Local Apperceive Interaction Module can sense the disturbances of the agent current status and interactively communicate with peripheral virtual agents nearby with the help of artificial potential field, which will impact on other agents in reverse. Therefore, the module is the foundation and important part for swarm intelligence. As shown in figure 2, Local Apperceive Interaction Module is composed of four module components, Local Apperceive Module, Information Interaction Module, Action Planner and Optimal Action Directives.

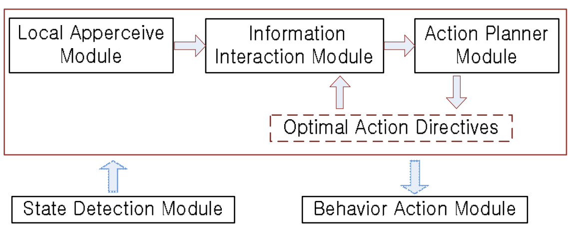

Figure 2 Local Apperceive Interaction Module

Local Apperceive Module receives the data which is transferred from State Detection Module, and gets the relevant intelligence virtual agent information such as geographic location, etc. Subsequently, Local Apperceive Module sends the relevant information to the Information Interaction Module, which will exchange information with other nearby intelligent agents in a certain radius. There are many selective behaviors in complex scenario, and the selection of many behaviors should be defined a behavior utility flow to each behaviors which is updated by local apperceive interaction. Action Planner receives transferred data about local scenario information from the Information Interaction Module, calculates using different weight functions and later sends the result to the Optimal Action Directives. Finally, the action directives are delivered to Behavior Action Module and to Information Interaction Module for further amendments.

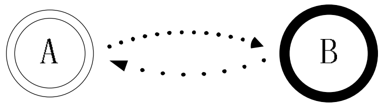

Figure 3 Example of Local Apperceive Interaction

For the interaction between intelligent agents, as shown in figure 3, the updated interaction function between agent A and B is:

$$F_m(t) = F_m^2(t-1) + w(t) \times \eta(1-\xi(t-1)) \qquad (1)$$

Among them, $F_m(t)$ represents the interaction relation between certain agent and other agents, with range of [0.0,1.0]. The higher value is, the more hospitable with other agents. And the initial value works as 0.5, which means that interaction relation between agents is undefined. W(t) represents the judgment of current interaction behavior, with range of [-1,1]. When w is less than 0, it means unfriendly interaction behavior; while w large than 0 means friendly interaction behavior. η determines the speed of interaction relation development, with range of [0.02, 0.05] after tests. ξ represents confidence level of the iteration relation during interactive experience with other agents, with range of [0,1.0], and the dynamic changes of ξ parameters which is shown as follows.

$$\xi(t) = \xi(t-1) + a(1-|w(t) - F_m(t-1)|) \qquad (2)$$

Among them, $\xi(t)$ represents a new confidence level while a learning rate. And a is defined as the range of [0, 0.02]. Local apperceive interaction function can dynamically sense the disturbances of the agent current status and interactively effective communicate with peripheral virtual agents nearby.

3.2 Active Learning Module

On basis of state detection information and corresponding action made by Behavior Action Module, Active Learning Module can obtain new knowledge through inference and calculus with knowledge evolution and evaluation rules. It will affect the intelligent agent action conversely, which is shown in figure 4.

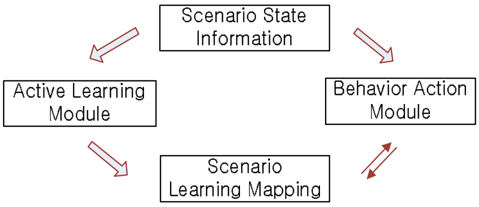

Figure 4 Workflow of Active Learning Module

With returned event-handling information and scenario status information, Active Learning Module can calculate and ratiocinate using between environmental and knowledge information mutual map concerns which are stored in scenario knowledge mapping library. If there is new state information and user events, the module will obtain new knowledge and get action functions with different weights according to the knowledge evolution rules. Therefore, intelligent virtual agent makes corresponding active behavior as external environment changing, with the purpose of adapting to dynamic complexity environment. Active Learning Module makes effective management of complex scenario knowledge using production rules method. The expression of complex scenario knowledge based on production rules method is IF (Condition) THEN (Conclusion), and current accuracy is set to 1 as default value according to uncertain fuzzy judgment during reasoning process. Production rules in scenario knowledge mapping library can be modified by users. Mapping control system uses reasoning process of forward inference mechanism primarily and backwards direction auxiliary as and graph search strategy. Active Learning Module using knowledge acquisition and knowledge evolution improved the self-regulation of behavior mechanism significantly.

3.3 Behavior Action Module & State Detection Module

Detecting and receiving local Scenario information, group interaction information and user event information in real-time, State Detection Module can submit the detection information for knowledge learning component in Active Learning Module. With the detection information, Behavior Action Module can make appropriate action smoothly. State detection can collect local virtual scenario information, such as environmental changed information due to the varying weather and temperature. It is necessary for the collection of intelligent agent local scenario interaction information and motion status information, and is also as resource for the other agents to make action and knowledge learning.

According to the information provided by the external environment and intelligent agent learning, Behavior Action Module optimizes the agent action and conducts the planned action generated by the IVA system. As the integration of received State Detection Module information, intelligent virtual agent can search feasibility path using A* algorithm and make reasonable action with reference to the new knowledge and determined interactions, such as avoiding sleet and driving livestock. Realization process consists of action control procedures and mathematical computation including displacement and rotation angle during move, which is also do follow-up action based on the events triggered by user.

4. Implementation

4.1 Intelligent Virtual Agents System

The IVA System based on Unity3D platform and MySQL 5.0 database, is realized by key technologies of active learning and local apperception in Seoul city, a complex virtual environment which is shown partly in the following figure 5.

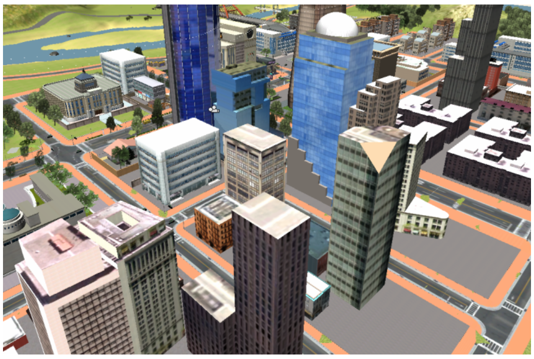

Figure 5 Intelligent Virtual Agents System

The instance mainly focuses on further research of action behavior study and Decision-making mechanism during information interaction among intelligent agents in the prototype system. It is assumed that the antagonistic relation exists only between vehicle and virtual human being, while friendly relations between virtual human being which are described completely in the next section. The friendly value between virtual human is defined by the real number of [0,1], and is dynamic updated as local apperceive interaction. Virtual human can apperceive current state by local scenario apperceive function and interact with other virtual human within a range.

Table 1 Main Interface in IVA System

Interface	Main Function	Describe Function
Child	(1) walkChild( ) (2) interactionLocal( ) (3) compareBrav ( ) (4) crossLine ( ) (5) changeBravery( )	(1) child walk behaviour function; (2) interaction with others in local area; (3) compare bravery value with the road line; (4) the behaviour of cross road event; (5) return new bravery value.
Sister	(1) walkSister( ) (2) interactionLocal( ) (3) ChildAbsence( ) (4) trendChild( ) (5)changAppScop ( )	(1) sister walk behaviour function; (2) interaction with others in local area; (3) absence action from sister scope; (4) head for child; (5) apperceive scope value change when trend event comes.

As shown in the system, the intelligent agents are child and sister detailed described in the paper. Child is walking during the continuous interaction with sister. The child can do some emergency events, such as crossed the street, when the distance between child and sister is longer than apperceive critical value. Meanwhile, the child can make Self-regulated Learning according to knowledge acquisition and knowledge evolution, and make the specific behavior decision by the brave value and danger value. There are many selective behaviors for the child in complex scenario, and the selection of many behaviors should be defined a behavior utility flow to each behaviors which is updated by local apperceive interaction. And the child can select the appropriate action according to the behavior utility flow finally. Active learning uses action functions with different weights to make active behavior correspondingly as the environment changed.

4.2 Random Walking without Interaction

With the purpose of comparing with the agent of local apperceive interaction in the next section, the classic model of how agent move in geometric spaces begins with randomness. The model is a two-dimensional walk which is simply a random deviation from a straight-line which represents the forward direction. This direction is the general intentionality of the walk which is positioned in two-dimensional space.

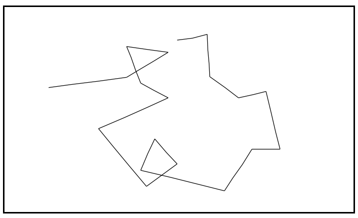

Figure 6 Random walking without interaction in two dimension

In figure 6, the basic model without consideration of learning and interaction function has a random behavior, and the trajectory of movement is chaotic, which is the basic movement. Next, we will make such walks more purposive by embedding some utility into agent structure.

4.3 Local Apperceive Interaction & Active Learning

Intelligent agent makes corresponding active behavior as external environment changed, with the purpose of adapting to dynamic complexity of virtual environment changes. In the prototype system, humans have the different sensing range. Child can acquires new knowledge from across the street which influences agents behavior decisions in return. Meanwhile, the safe distance between child and sister is always changing due to the feature of sudden public incident.

Figure 7 Function of local apperceive interaction and active learning

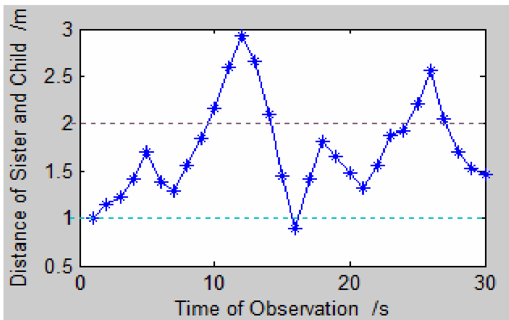

Figure 8 Dynamic changing distance between child and sister

In figure 8, two horizontal threads represent initial values and apperceive critical value of human distance. There will be emergency events by the child, such as crossed the street, when the distance between them is longer than apperceive critical value. The result shows that sister can communicate with child immediately when she found his absence, and child will change the direction autonomy for the sister when local apperceive interaction is executed, as shown in figure 8, with the purpose of local apperceive interaction and behavior regulation.

5. Conclusion

In the paper, we design and implement the IVA system architecture based on active learning and local apperceive interaction using knowledge acquisition and knowledge evolution module. Local apperceive interaction function can dynamically sense the disturbances of the agent current status and interactively effective communicate with peripheral virtual agents nearby. Finally, the practical application shows that the IVA framework improves adaptation to the complex virtual environment prominently. However, the emotion-based agent has not be considered currently and community interaction and communication among IVA have not taken into account. The further work will be focused on the analysis of stream data generated by the IVA system, which can ameliorate learning and actions through discovering valuable rules or models from huge raw data.

Acknowledgments

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