Towards reactive navigation and attention skills for 3D intelligent characters *

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Abstract. This paper presents a neural design which is able to provide the necessary reactive navigation and attention skills for 3D embodied agents (virtual humanoids or characters). Based on Grossberg's neural model of conditioning [6], as recently implemented by Chang and Gaudiando [7], and according to the Adaptative Resonance Theory (ART) and the neuroscientific concepts associated, the neural design introduced has been divided in two main phases. Firstly, an environment-categorization phase, where an on-line pattern recognition and categorization of the current agent sensory input data is carried out by a self organizing neural network, which will finally provide the agent's short term memory layer(STM). Secondly, and based on the classical conditioning paradigm, the model will associate the interesting STM states, from the navigation or attention points of view, to finally simulate these necessary skills for 3D characters or humanoids. Finally, we will show some experimental navigational results, through the integration of the model presented in 3D virtual environments.

1 Introduction

Intelligent Robotics and Intelligent Virtual Environments(IVE) share the lack of designing agents capable of finding paths free of obstacles in order to satisfy their high level goals. Furthermore, one of the main tasks of any mobil agent, including humans, is navigation. In the majority of applications where 3D embodied agents are required, such as games or real time graphic simulations, this navigation problem is normally solved using any plausible global search technique, which is normally applied under classical static environmental assumptions [9]. A more reduced set of contributions in this field considers navigation as a local agent

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problem, simulating a realistic information flow from the environment to the agent, and easily computed through the classical *sense/think/act* agent cycle.

From robotics, Latombe et al. have combined 2D path-planning techniques with a rule-based system for modelling memory and synthetic vision/perception in virtual human simulations[4].

Tu and Terzopoulos implemented a realistic simulation of autonomous artificial fish combining a raycasting vision system with physical-based locomotion [5]. This system has been also applied to 3D virtual humans [12].

Noser et al. presented a synthetic vision system that uses object-false coloring and dynamic octrees to represent the visual memory of the character who navigates combining global and local techniques[2].

As nowadays, the increasing graphic realism of 3D characters has generated corresponding expectations in terms of character's behaviour (including the low-level ones), our main research interest is to provide for the adequated AI formalisms in order to reproduce and display the neccesary intelligence related to the skills cited.

In 3D environments, agents can perfectly access to the complete visual data base, so local sensorization is not really a requirement. However, local methods are clearly more appropriate for managing the necessary information flow to simulate reactive behaviours, such as navigation in dynamic environments or visual attention. For instance, the process of filtering visual sensory information and selecting the most interest objects from the environment to attend, that is, visual attention would be a globally untractable problem for complex environments. Furthermore, global navigation techniques for 3D intelligent virtual agents (IVAs) present the following problems:

- Reactivity: During navigation, the agent's target could change, for instance it could detect a virtual friend, or escape from a new enemy. Dynamic virtual environment simulations, where obstacles or agents could appear anytime, suggest the avoidance of global path calculations.
- Uncertainty: The agents could not have global information about their environment. This must be a requirement in virtual humans, which must only remember the places previously visited, in order to perform realistic simulations, such as in supermarkets, etc.
- Realism: Depending on the environment discretization (2D-grid, quadtrees, octrees) the global path obtained will contain the set of cell-centroids, which the agent must visit to finally achieve its position goal. The visualization of this path will have a low realism degree and normally an extra path-smooth phase will be also required.

Bearing this in mind, and although low-level navigation and attention behaviours for 3D characters depend on the specific application, we can identify these essential requirements:

- Reachability: For any goal position, the agent must be able to reach it autonomously.

– Collision Avoidance: Agents must reach their goal positions without colliding with any obstacle or agent.
– Replanning: Goal position can change during navigation so flexible navigation will be also required.
– Lifelike paths: Optimization criteria considered typically in global navigation algorithms, (minimum distance/energy), must be blended with local information in order to achieve lifelike paths instead of minimum ones.
– Lifelike attention: In every simulation cycle the agent must attend to interesting objects/agents, according to their properties (ej.: type, size, color, speed, direction, ...) .

The rest of this paper is organized as follows, firstly we will present the sensory agent system and the feedforward scheme introduced as the basis of the neural design proposed. Then we will explain this design focussing mainly on, the on-line environment categorization performed by a FuzzyArt Neural Network, and the conditioning machanisms introduced later. Finally we will also show the experimental navigation results obtained during simulation time, which have demonstrated a good potential for scaling the neural model up.

2 The sensory agent system

Intelligent robots or virtual characters with a set of sensors and memory skills must be able to explore unknown environments, and incrementally build their own internal model of the world. In this way, the main information channel between the environment and the agent, should be provided by the sensory agent system.Furthermore, 3D humanoids must take this into account, simulating a realistic information flow from the environment to the agent, instead of creating omniscient agents.

As we know, synthetic vision differs from vision computations for real robots, since we can skip all of the problems of distance detection, pattern recognition, and noisy images [4]. This allow us to implement a reasonable model of visual information flow that operates in real time systems. We are considering virtual vision sensors as a simple pyramidical culling volume from the agent point of view. According to this, in each agent's simulation cycle, every object or agent accepted by its vision cull-test, that is, the visible objects and agents, will shape an observation vector within semantic information relating to the object/agent (direction, distance, size, color, ...). In order to introduce high level information to be used by the planner system [11], we have also included relevant information about its state, for instance `door(open/closed)`(Figure 1). This semantic-vector approach is similar to Latombe's perception-based navigation system, where visual observations are simulated using an output vector provided by the vision module as well [4]. As Figure 1 shows, each observation corresponds to a couple of vectors, that is, the rays that cover completely the obstacle from the agent's point of view. This information will be useful for navigation tasks in two ways, firstly as the necessary patterns to represent and categorize the environment, in order to perceive and detect them in the future, and secondly to inform the navigation system about the directions that will drive the agent to a collision situation.

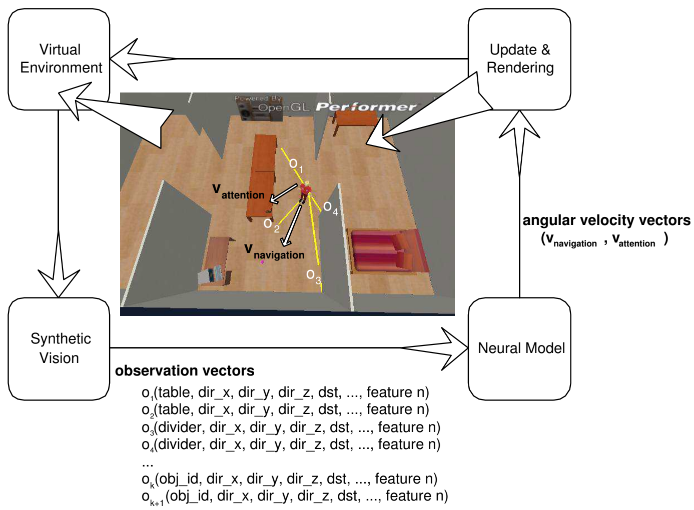

Fig. 1. Basic agent loop

In the next section we will review the neural model we are using to categorize the environment, as a generic machanism for the agent's perception and situation detection.

3 The Neural Design

The neural design proposed is based on a simple 3-layer feedforward model presented in [10]. The first layer (goal following) will compute the alignment of each neuron, as a vector of an angular map, to the goal. Then, in the correction layer, and according to the sensory information provided, we can reprimand the neurons which would locate the agent on a collision course. Finally both contributions are taken into account in the motor layer, which will search for the neuron with the maximum activation value. As we will see in the results section, this reactive scheme can be adequate for 3D virtual humans, and let us consider the possibility of parametrizing several important factors, such as, the security distance to objects. However, it could fail in some situations (Figure 4), local minima, etc, so we have complete the correction layer with the following model.

3.1 Synthetic Perception and Short Term Memory

Human vision is a complex process where input data is taken from saccadic eye movements and then processed in different areas of visual and prefrontal cortex. During this process a high level classification occurs resulting in a number of categories which will represent the state of the agent's environment, from its point of view. The Adaptative Resonance Theory (ART) has been used for this task as a well known human cognitive information processing model and according to this model, each agent will have a Fuzzy ART Neural Network for managing this categorization, which will give the agent the possibility of learning new categories, or situations to consider, without forgetting familiar ones [6].

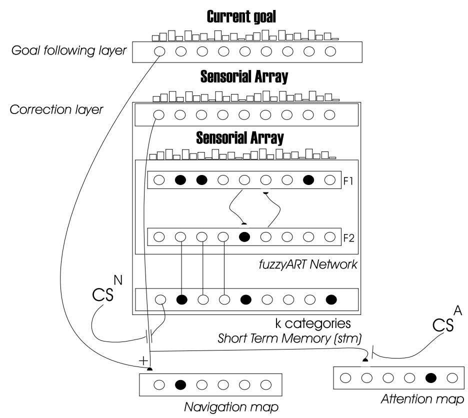

Fig. 2. Neural design for agent attentive navigation

As Carpenter&Grossberg pointed out, the Fuzzy-ART system tries to allocate the current sensory input sample in one of the familiar categories previously learned. When agreeing with the vigilance parameter, typically included in ART systems, this sample cannot be committed to any of the current categories, the model will create a new one. In this first learning step, the observation vectors (Figure 2) will be sent to the agent which will *take a look* at its environment for ascertaining its variability. As a self organizing neural network, this learning step can be carried out on-line, that is, in real time. Bearing this in mind, the agent will learn the variability of objects from its environment to finally manage a finite number of self developed categories which will represent several situations that the agent is interested in controlling, such us, a new interesting objects/ agents to attend, or a plausible collision situation.

Typically, in ART systems a single input pattern is able to activate only one category, however, a complete reasoning cycle for 3D IVA's must imply the sequential activation of different categories. According to this, the active categories will be stored in a new layer (STM) which will finally represent the agent's short term memory in real time (Figure 2).

The next problem will consist in finding the right associations between specific STM states and the 3D agent motor layers, considered as normal angular velocity vector maps. To achieve this, the model must learn *when* and *how* to map its current STM state into the navigation and attention motor layers. This process will be based on the classical conditioning paradigm and it will also be neccesary to consider specific conditioning learning signals in both associations: STM - navigation layer (CSn) and STM - attention layer(CSa) [7](Figure 2).

In a first mapping (STM-navigation association), the model will help the correction layer of the basic feedforward scheme to finally control the angular velocity vector of the agent's body, so that, the training will be oriented to detect and associate collision situations with the navigation output vector.

In parallel (currently under construction), a second mapping will simulate visual human attention. Again, associating the right stimuli, the velocity vector map considered for the attention layer will control the final character's head orientation in real time. For a further explanation about the neural model presented see [10].

4 Experimental Results

The model described has been implmented in C++ and has been integrated with two kinds of 3D environments, such as, SGI-IrisPerformer API and the Unreal Tournament 3D virtual environment graphic engine. The first results presented in [10] was concerned with the basic feedforward model, and no learning was carried out. This system has been upgraded and tested in several situations, as Figure 3 shows, where through classical parametrization, this basic model let's us consider the possibility to include internal agent variables, such as stress, or a security factor, in order to help in avoiding any obstacle (Figure 3).

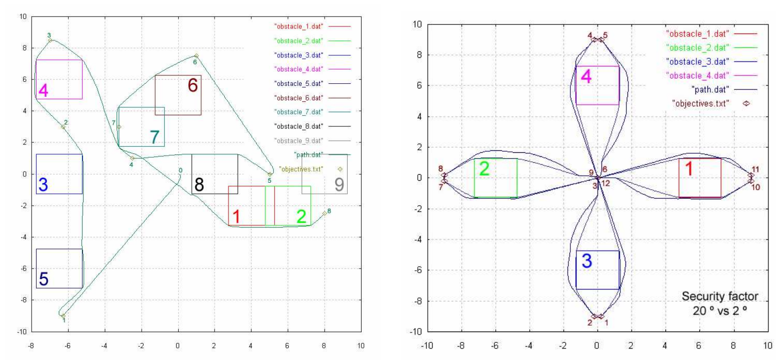

Fig. 3. Paths obtained in several test situations

Figure 4 in its first loop, shows the behaviour founded without considering the security factor mentioned, in this situation, when the agent is to close to the bounding box of the object represented and no categories has been learned, it can loose its sensory information and go forward its goal, unfortunately, passing over the obstacle. As the categorization performed in the STM layer is sensitive to conflict situations, this let's us implement the associative learning already explained, in order to control them properly. This is shown in the second loop of its 7-step plan when a similar collision situation is faced the second time, the agent can now recognize it and correct it, avoiding the collision situation previously learned.

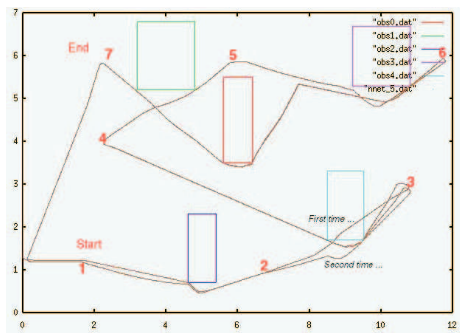

Fig. 4. Learning on-line from past situations

In order to visualize the resultant character's behaviours, the system has been also integrated in the Unreal Tournament 3D graphics engine, where basically the neural model should send via UDP sockets the current position and orientation to the game engine. These data are managed by several UnrealScripts, the engine's scripting lenguage, to finally locate the 3D character in the virtual environment (Figure 4).

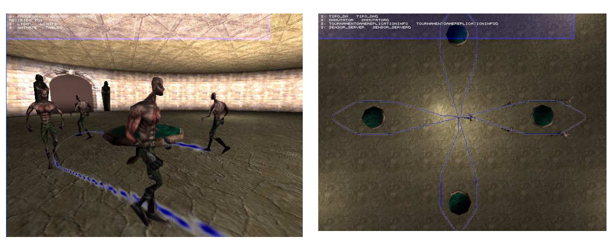

Fig. 5. Paths follwed by the 3D agent in a UT based 3D virtual environment

5 Conclusions

Neural approaches have been previously introduced in 3D intelligent creatures, mainly on solving dynamical systems for computer animations [5]. However, the majority of 3D agent architectures are focused on low cost global techniques to solve navigation problems and approaches from neuroscience are less frequent in 3D virtual worlds. A new neuromodel approach has been presented for covering visual attention and navigation for 3D intelligent virtual agents, such us 3D virtual humans but it could be also adapted to robotics.

According to the results obtained, we expect to undertake new experiments focussing on navigation reactions, for example avoiding dynamic obstacles or agents, and finally including the necessary machanisms for visual attention in 3D humanoids.

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