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Three-layered Case-based Reasoning Cycles for Autonomous Virtual Agent Moving Through 3D Virtual Environment

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***Abstract*— In this paper we describe three-layered case-based reasoning cycles for autonomous virtual agent (AVA) moving through 3D virtual environment. The AVA and virtual environment interact at each of a sequence of interaction loops. The AVA selects the appropriate actions based on a previous interaction experience represented in the form of cases. Cases include observations of the virtual environment as well as behavior routines that represent the solution component of cases. The AVA that continuously interacts with a virtual environment must be able to autonomously create new situation cases based on its perception of the local virtual environment in order to select the appropriate actions to achieve the goal state.**

***Index Terms*— autonomous virtual agent, case-based reasoning, three-layered cycles, virtual environment.**

I. Introduction

The development of Autonomous Virtual Agents (AVAs) that use prior experience in virtual environments is very helpful in many areas. A number of researchers have studied virtual agents with internal sensory and storage mechanisms [1, 2].

A. Case-based Reasoning

Solving a problem by Case-based Reasoning (CBR) involves obtaining a problem description, measuring the similarity of the current problem to previous problems stored in a casebase with their known solutions, retrieving one or more similar cases, and attempting to reuse the solution of one of the retrieved cases, possibly after adapting it to account for differences in problem descriptions [3]. The solution proposed by the system is then evaluated (e.g.., by being applied to the initial problem or assessed by a domain expert). The new problem description and its solution can then be retained as a new case, and the system has learned to solve a new problem [3]-[5].

B. Virtual Environment and Synthetic Vision

Objects are the building blocks of the 3D virtual environment (see Fig. 1). Examples of objects include walls, doors, floors, tables, chairs etc. The surface is assumed to be flat in the implementation described here. The virtual agent acquires image data from a scene, and the scene is graphically rendered from the AVA's point of view. We have developed an approximate model for synthetic vision that is suitable for moving through the 3D virtual environment. Synthetic vision generally involves determining which object surfaces in the environment are currently visible to a virtual agent. This problem can be viewed as calculating all visible surfaces from a particular viewpoint given a collection of objects in 3D. We adopt an approach to synthetic vision similar to the one described in [6], and [7].

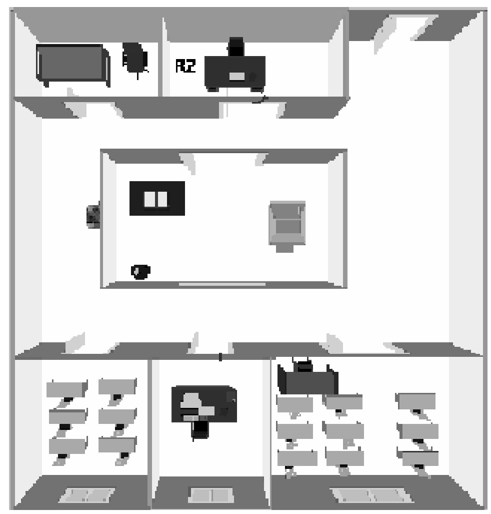

Fig. 1. Virtual Environment

Synthetic vision stimuli from the virtual environment are generated as a consequence of a previously selected action for focusing of attention. Synthetic perception stimuli are synthesized input *n*-tuples that represent an integrated description of relevant aspects of virtual environments E in the current situation. For example, if an agent selects an action for focusing of attention $f=(A_1, A_2,\ldots, A_n)$, then a perception generator generates a synthetic perception stimulus $sp_f=(v_1, v_2 \ldots,v_n)$, $v_i \in D_i$, $i=1,2,\ldots n,$ as a consequence of the action denoted as f and where D_i is a domain of a perception attribute A_i.

Throughout each interaction loop, the AVA receives a perception stimulus, $p_i \in P$, where P is a set of all possible perception stimuli, and on that basis selects an action $a \in A$, where A is the set of all possible actins. The AVA selects an appropriate action by using case-based reasoning and after that the agent executes the action. One interaction loop later, as a consequence of its previous action, the AVA finds itself in a new situation (Fig. 2).

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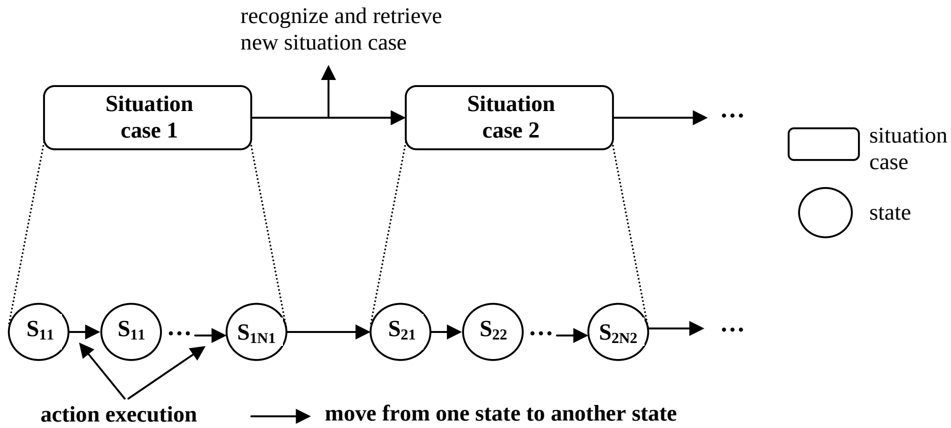

Fig. 2. As a consequence of its previous action, the AVA finds itself in a new situation

II. Case-based Representation of the AVA's Interaction Experience

Formally, an AVA interaction experience ex_i until i-th interaction step can be represented by n-tuple $ex_i=(p_1, a_1, p_2, a_2, \ldots p_i, a_i, \ldots p_i, a_i)$. The n-tuple ex_i can be defined inductively as:

- $ex_1=(p_1,s_1)$,
- $ex_i=(ex_{i-1}, p_i, s_i)$, $i=2,3,\ldots$.

The AVA selects the appropriate actions based on a previous interaction experience. Of course, it is not appropriate to store all perception experience. The approach to representing interaction experience is to extract cases from continuous AVA-environment interaction. Cases include observations of the virtual environment as well as behavior routines that represent the solution component of cases. In our representation scheme, cases are classified as plan and situation cases [8]. Furthermore, situation cases are classified as contextual and action cases (Fig. 3).

Plan cases are used to support reasoning processes at planning abstraction level. As a result of reasoning processes at plan level an SCBR agent select an appropriate *plan behavior routine* (Fig. 4). On the other side, situation cases are used to support reasoning processes at contextual and action abstraction levels. As a result of reasoning processes at contextual and action levels, the AVA selects appropriate contextual and action behavior routines. All types of behavior routines are represented as n-tuples $b=(b_1, b_2, \ldots b_j, \ldots b_n)$, $1\leq j\leq n$, where b_i denotes a *plan* or *contextual* intention (*plan and contextual behavior routine*) or b_i denotes an action (*action behavior routine*).

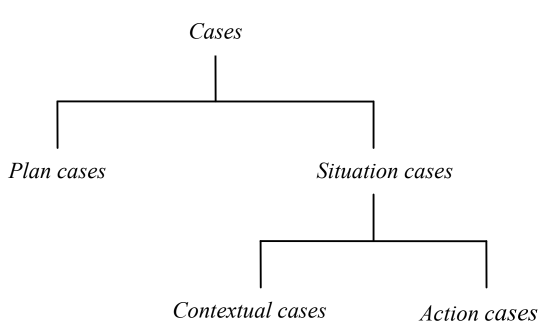

Fig. 3. Classification of cases

III. Three-layered Case-based Reasoning Cycles

In this section, we describe three-layered case-based reasoning cycles for AVAs moving through 3D virtual environment. First, we introduce a connectivity function cf that is used throughout case-based reasoning cycles. This function connects intentions and actions for focusing of attention. A connectivity function cf defines the mapping from a set of all intentions I to a set of all actions for focusing of attention F, $cf: I \to F$.

The phases of three-layered case-based reasoning cycles are now described [9].

Create a new plan case: A user defines a new mission of an AVA**.** A new mission is defined as a goal state of the AVA.

Retrieve a plan case: The plan case similar to the new plan case is retrieved from the casebase. Plan behavior routines $b_p=(i_{p1}, i_{p2}, \ldots i_{pn})$ is obtained from the retrieved case and adapted to the new goal state.

Create a new contextual case: From a plan behavior routine the AVA selects a current plan intention i_p. Using a connectivity function, a contextual action for focusing of attention is selected, $f=cf(i_p)$, and the AVA forms a synthetic perception sp_f based on synthetic vision stimuli. In this way, the description component of the new contextual case is created, $d_c=(f, sp_f)$.

Retrieve a contextual case: The contextual case similar to the new contextual case is retrieved from the casebase. Contextual behavior routines $b_c=(i_{c1}, i_{c2}, \ldots i_{cn})$ is obtained from the retrieved case. The behavior routine is adapted to the new conditions.

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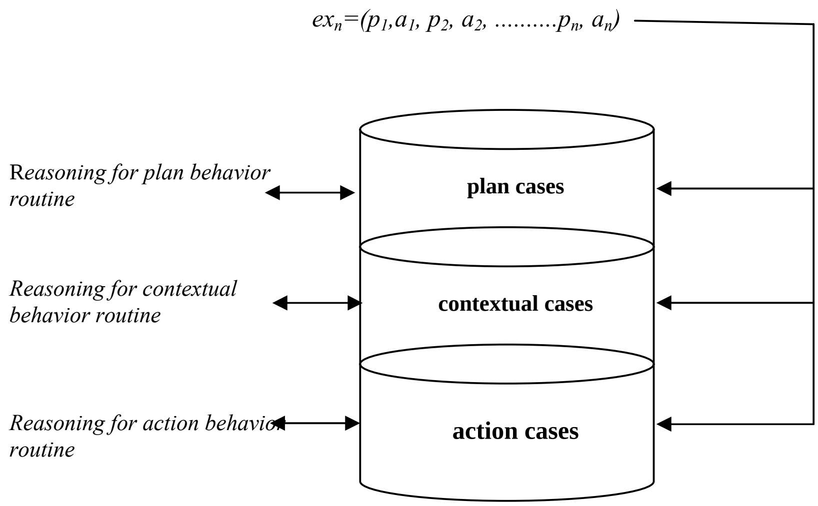


Fig. 4. As a result of reasoning processes at plan, contextual and action levels, an AVA selects an appropriate *plan, contextual and action behavior routine, respectively.* All cases are extracted from interaction experience ex_i.

Create a new action case: Using a connectivity function *cf* an action for focusing of attention *f* is selected and the AVA forms a synthetic perception sp_f based on synthetic vision stimuli. Thus, the description component of the new action case is created, $d_a=(f, sp_f)$.

Retrieve an action case: An action case similar to the new action case is retrieved from the casebase. Action behavior routine $b_a=(a_1, a_2, \ldots a_n)$ is obtained from the retrieved case. The behavior routine is adapted to the new conditions. An action behavior routine b_a is an ordered sequence of actions a_i, $i=1,2,\ldots n$.

Reuse of an action case: In this phase, the action behavior routine $b_a=(a_1,a_2,\ldots.a_n)$ is used by a step by step approach. In this phase, after each selected action a_i, the action behavior routine b_a is evaluated. It must be checked if the behavior routine as a plan to achieve a current contextual intention is adequate. When all actions are selected and executed, the action for focusing of attention to the outcome of the action behavior routine is selected. The AVA receives a perception stimulus that represents the outcome component of the new action case.

Retain a new action case: The new action case is stored in the casebase.

Revise a contextual behavior routine: In this phase, before selection of a new contextual intention i_c from the contextual behavior routine b_c, this routine is revised and eventually adapted. If the contextual behavior routine $b_c=(i_{c1}, i_{c2}, \ldots i_{cn})$ contains unrealized contextual intentions, then the reasoning goes to the phase <*Create new action case*>, else the AVA selects an action for focusing of attention to the outcome of the current contextual routine. As a result of the selected action, the AVA receives a perception stimulus that represents the outcome component of the new contextual case. The AVA's reasoning cycles continue with the phase denoted as <*Retain contextual case*>.

Retain a new contextual case: The new contextual case is stored in the casebase. The AVA selects a next plan intention from the current plan behavior routine b_p, and reasoning cycles continue with the phase denoted *as* <*Create new contextual case*>.

Revise a plan behavior routine: The AVA selects an action for focusing of attention to the outcome of the current plan behavior routine b_p. As a result of the selected action, the AVA receives a perception stimulus q_{pi} that represents the element of outcome component of the new plan case. In this phase, before selection of a new plan intention i_p from the plan behavior routine b_p, this routine is revised and eventually adapted. If the plan behavior routine $b_p=(i_{p1}, i_{p2}, \ldots i_{pn})$ contains unrealized plan intentions, then the reasoning goes to the phase <*Create new contextual case*>, else the AVA selects an action for focusing of attention to the outcome of the current plan behavior routine b_p. As a result of the selected action, the AVA receives a perception stimulus that represents the element of outcome component of the new plan case. The AVA's reasoning cycles continue with the phase denoted as <*Retain plan case*>.

Retain a new plan case: The new plan case is stored in the casebase. The AVA asks a definition of the new mission from a user and reasoning cycles continue with the phase denoted *as* <*Create a new plan case*>.

IV. An Illustration and Experimental Results

A. An Illustration

To help in understanding how three-layered case-based reasoning cycles work, we show one situation from autonomous navigation task. The AVA's planning module generates a current plan intention, based on plan cases. The solution component of plan cases is an ordered sequence of plan intentions. The AVA selects a current plan intention i_p. Assume that the current plan intention is "*exit-from-room*". This intention directs the AVA's attention to the relevant perception attributes: distance from obstacle to the left wall (L) and distance from obstacle to the right wall (R) (see Fig. 5). Formally, the AVA selects the contextual action for focusing of attention $f=(L, R)$ and forms a synthetic perception sp_f =(1, 2) based on synthetic vision stimuli. Thus, the new contextual case is created $c_c=(d_p, ?, ?)$, $d_p=(f, sp_f)$, where *?* denotes temporarily undefined components. Then, the most similar contextual case is retrieved from the casebase $rc_c=(d_c, b_c, q_c)$, and the solution component b_c is adapted to the new conditions. The adapted solution component of the retrieved case is an ordered sequence of contextual intentions. Assume, that this component is b_c=(*mrao, md*) where

– *mrao* denotes the contextual intention "*move-right–to–avoid -obstacle*", and
– *md* denotes the contextual intention "*move- to-door*".

The AVA selects the intention *mrao* that directs the attention to the relevant perception attributes: distance from obstacle *(D)*, angle to front-right obstacle's corner (θ), and distance from right wall *(W)* (see Fig. 5). Formally, the AVA selects the action for focusing of attention $f=(D, \theta, W)$. Then, the AVA forms a synthetic perception sp_f =(1.5, 1, 3). The action for focusing of attention f and the synthetic perception sp_f are elements of the new action case's description component, $d_a=(f, sp_f)$. Then, the most similar action case is retrieved, $c_a=(d_a, b_a, q_a)$ and the solution component b_a is adapted to the new conditions. The adapted solution component b_a is an ordered sequence of actions. The AVA selects the actions from b_a and moves through the virtual environment.

When all actions are selected and executed, the action for focusing of attention to the outcome of the action behavior routine is selected. As a result of the selected action, the AVA receives a perception stimulus that represents the outcome component of the new action case. The new action case is stored in the casebase. Before selection of the intention *md* (*"moving-to-door"*) from the contextual behavior routine b_c, this routine is revised and eventually adapted. When all contextual intentions from the contextual behavior routine b_c are achieved, the AVA selects the action for focusing of attention to the outcome of the current contextual behavior routine. As a result of the selected action, the AVA receives a perception stimulus that represents the outcome component of the new contextual case. The new contextual case is stored in the casebase. Furthermore, the AVA selects a next plan intention i_p from the plan behavior routine b_p, and case-based reasoning cycles are repeated throughout the new contextual instance similarly as previously described for achieving the plan intention "*exit-from-room*".

B. Experimental Results

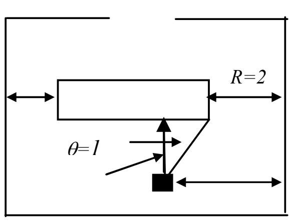
In order to evaluate the described three-layered case-based reasoning cycles, we have experimented and analyzed mission success rate. The experiments performed with AVA were done to verify that it could meet certain requirements needed to autonomously carry out a navigational mission in virtual environment. These requirements include: being able to navigate to a designated room; being able to autonomously create new situation cases; being able to avoid obstacles by going around the obstacles, etc.

All of the experiments had the same basic format, though the details of the AVA's starting position and orientation, the positions of obstacles, and the AVA's goal position and orientation. The AVA's positions are given in *X-Y* coordinates. Three different casebase configurations were tried in order to investigate the mission success rate:

1. $|CB_p|=20$, $|CB_c|=30$, and $|CB_a|=30$
2. $|CB_p|=35$, $|CB_c|=50$, and $|CB_a|=50$
3. $|CB_p|=50$, $|CB_c|=80$, and $|CB_a|=70$

where $|CB_p|$, $|CB_c|$, and $|CB_a|$ denote the number of plan, contextual, and action cases, respectively. Each casebase configuration has been tested by using 30 AVA's navigation missions. Table I shows a summary of experimental results.

(a)



(b)

perception attributes:

R distance from obstacle to the right wall,
L distance from obstacle to the left wall,
θ angle to the front-right corner of the obstacle,
D distance from the obstacle,
W distance from current position to the right wall,

current position and orientation of the AVA.

Fig. 5. An illustration of the perception attributes for autonomous navigation in indoor environments. (a) A simulated vision from the current position of the robot (b) 2D representation of the relevant perception attributes for the current situation

Table I. Experimental results

Casebase size	Unsuccesseful missions		Succesful missions	
	Number	Rate	Number	Rate
$\lvert CB_p\rvert=20$, $\lvert CB_c\rvert=30, \lvert CB_a\rvert=30$	9	30%	21	70%
$\lvert CB_p\rvert=35$, $\lvert CB_c\rvert=50, \lvert CB_a\rvert=50$	2	6,7%	28	93,3%
$\lvert CB_p\rvert=50$, $\lvert CB_c\rvert=80, \lvert CB_a\rvert=70$	1	3,3%	29	96,7%

We can see that the experimental results obtained using the three-layered approaches increases mission success rate with increasing number of previously stored cases.

V. Conclusions and Future Work

The development of Autonomous Virtual Agents (AVAs) that use prior experience in virtual environments is very helpful in many areas. A number of challenges are raised in developing a system incorporaiting AVAs. One of the most important challenges facing today's AVA's development is the appropriate representation and usage of prior interaction experience. In this paper, we have described three-layered case-based reasoning cycles for autonomous virtual agent moving through 3D virtual environment. The AVA selects the appropriate actions based on a previous interaction experience represented in the form of cases. Experimental results obtained using the presented approach increases mission success rate with increasing number of previously stored cases. Much future work remains. We are planning to extend this research and involve different types of virtual environments.

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