An Agent's Action Selection Strategy by Using Case-based Reasoning and Simulated Vision

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***Abstract*— This paper presents an approach to agent's action selection strategy called stepwise case-based reasoning (SCBR). In this paper an agent that roams in 3D synthetic world is called an SCBR agent. An SCBR agent is an entity that selects the next action based on previous interaction experience and on simulated vision. An SCBR agent's interaction experience is represented in the form of two different types of cases: *plan cases* and *contextual cases*.**

***Index Terms*— agent, action selection, simulated vision.**

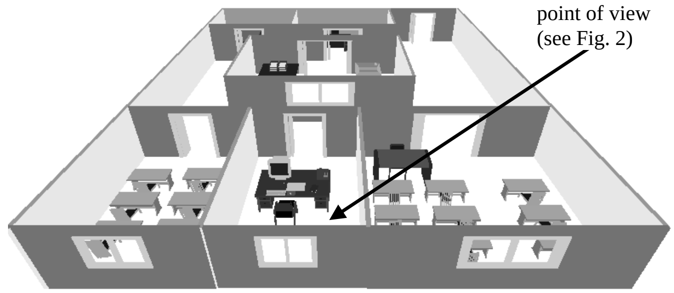

Fig. 1. The 3D synthetic world. Objects are the building blocks of the 3D synthetic world. Examples of objects include walls, doors, floors, tables, chairs etc.

I. Introduction

Case-based reasoning (CBR) is a type of reasoning based on the reused past experiences called cases [1, 2]. In general, a case consists of *a problem, its solution* and *an outcome*. The basic idea of CBR is that the solution of successful cases should be reused as a basis for future similar problems [2]. A CBR agent that continuously interacts with an environment must be able to autonomously create new cases based on its perception of the local environment in order to select the appropriate actions to achieve the current mission goal [3]. Laza and Corchado shows how to build deliberative BDI agents (*belief, desire, and intention*) using a case-based reasoning model [4]. Olivia et al. [5] also describe a framework that integrates CBR capabilities in a BDI architecture. The relationships between autonomous systems and CBR systems constitute the research reported in [6], [7], and [8]. This paper describes a case-based approach to action selection for an autonomous agent acting in 3D synthetic worlds. This approach is called stepwise case-based reasoning (SCBR).

II. Synthetic World, Simulated Vision and Model of Interaction

Synthetic world. Objects are the building blocks of the 3D synthetic world. Examples of objects include walls, doors, floors, tables, chairs etc. The surface is assumed to be flat in the implementation described here (see Fig. 1). In order to qualitatively evaluate the SCBR approach, we have developed a simulation environment. This simulation environment allows us to visually evaluate the progress of an SCBR agent while it runs through a predefined 3D synthetic world. The SCBR agent acquires image data from a scene, and the scene is graphically rendered from the agent's point of view (see Fig. 1 and Fig. 2). The key idea is to somehow realistically model the flow of image sequences from the 3D synthetic world to the SCBR agent. In our simulation environment, we have developed an approximate model for simulated vision that is suitable for simulation purposes.

Simulated Vision. Simulated visual perception, also known as synthetic vision, can provide an appropriate means for an SCBR agent to reason based on what it perceives. Simulated visual perception generally involves determining which object surfaces in the 3D synthetic world are currently visible to an

Fig 2. A simulated vision from agent's point of view (see Fig. 1)

SCBR agent. This problem can be viewed as calculating all

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visible surfaces from a particular viewpoint given a collection of objects in 3D.

The SCBR agent has a limited perceptual range. Thus, computing the view object from an agent's current location involves intersecting all synthetic world geometry with the agent's cone of vision and performing removal of hidden surfaces to determine which objects are visible. There have been several proposals for simulated visual perception [9], [10]. Tu and Terzopoulos implemented a model of simulated vision for their artificial fishes based on ray casting. We adopt an approach to synthetic vision similar to the one described by Tu and Terzopoulos.

It is also important to model the basic limitations of agent's perception capabilities. The perceptual range is limited to a spherical angle extending to an effective radius [10].

Model of interaction. Now, we will briefly describe *the SCBR agent-3D synthetic world* interaction. The SCBR agent and synthetic world interact at each of a sequence of interaction loops. Each interaction loop includes the following phases:

1. perceive the synthetic world,
2. select an action, and
3. action execution.

Throughout each interaction loop, the SCBR agent 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 actions. One interaction loop later, as a consequence of its action, the SCBR agent finds itself in a new situation. Fig. 3 shows *the SCBR agent-3D synthetic world* interaction. The SCBR agent does not use case-based reasoning in each action selection phase of an interaction loop. Instead, throughout certain interaction loops, the SCBR agent routinely selects actions without reasoning processes. Throughout these interaction loops the SCBR agent uses behavior routines that are selected by case-based reasoning from a certain previous interaction loop. We define the concept

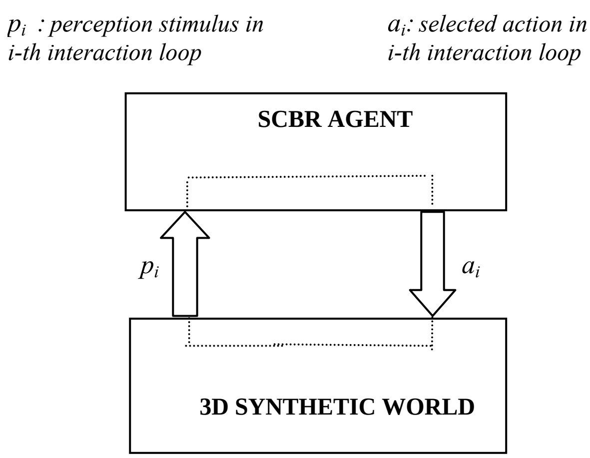

Fig. 3. The SCBR agent-3D synthetic world interaction loop. Each interaction loop includes the following phases: 1. perceive the 3D synthetic world, 2. select an action, and 3. execute the selected action

of behavior routine in Section 3.

An SCBR agent uses the two types of actions as follows: **internal actions for focusing of attention** and **external actions**.

Internal actions for focusing of attention. By applying this type of actions, an SCBR agent can autonomously create new contextual case that reflects changes in the 3D synthetic world. Formally, an action for focusing of attention f is an n-tuple $f=(A_1, A_2, \ldots A_n)$ where A_i is a perception attribute, $i=1,2,\ldots n$. A perception attribute is a relevant feature of the 3D synthetic world that is important for an SCBR agent's next action selection. An action for focusing of attention is an abstract representation of an SCBR agent's internal action.

External actions. An external action a is an n-tuple $a=(v_1, v_2, \ldots v_p) \in \mathbf{R}^p$ that represents manipulative actions selected by an SCBR agent that change state of the SCBR agent. For example, an SCBR autonomous navigation agent may have the defined an external action as three-tuple $a=(\Delta x, \Delta y, \Delta\theta)$ where Δx denotes the shift of an agent in X direction, Δy denotes the shift of an agent in Y direction and $\Delta\theta$ denotes the shift of an agent orientation.

III. PLAN CASES AND CONTEXTUAL CASES

A. Intentions and Behavior Routines

The term intention denotes a determination to act in a certain way or to do a certain thing. In the model of the SCBR agent, there are two types of intentions: *plan intentions* and *contextual intentions*. Plan intentions are planned in advance at the beginning of the current mission due to the fact that the synthetic world contains certain static structures that do not change over time. This is an opposite of the contextual intentions. A contextual intention represents an SCBR agent's desire that is the most appropriate for the given contextual conditions. Contextual intentions will have to be left unspecified until the situation in which they are required arises and relevant perception attributes of the local environment can be determined by selecting an appropriate internal action for focusing of attention. Plan intentions and contextual intentions are in hierarchical relationships. An example of a plan intention for autonomous navigation tasks is "*exit-from-room*". An example of a contextual intention is "*move-right-to-avoid-obstacle*".

Behavior routines. Behavior routines are defined as n-tuples $b=(i_1, i_2, \ldots i_j, \ldots i_n)$, $1 \le j \le n$, where the two types of n-tuples are possible. If all elements i_j, $1 \le j \le n$, in n-tuple denoted as b are *plan intentions*, then b is called *a plan behavior routine*. Furthermore, if all elements i_j, $1 \le j \le n$, in n-tuple b are contextual intentions, then b is called *a contextual behavior routine*.

B. Plan Cases

Most synthetic worlds contain structures that remain static during the lifetime of an agent. These static structures represent local environments and each local environment represents a particular context. An SCBR agent that performs stepwise case-based reasoning is adequate for the synthetic worlds that contain identifiable configurations (structures) of the local environment. In this paper, types of identifiable local environments are called *contextual classes*. Furthermore, concrete examples of local environments are called *contextual instances*. Examples of contextual classes and contextual instances for the autonomous navigation tasks are illustrated in Fig. 4.

A plan case c_p is a *three*-tuple $c_p=(d_p, b_p, q_p)$ where: d_p is *a description component*, b_p *is a solution component*, and q_p is *an outcome component*. *A description component* d_p is an *n*-tuple $d_p = (c_1, c_2, ..., c_i, ...c_n)$, $1 \le i \le n$, $c_i \in C$, where C denotes the set of all contextual instances. *A solution component* b_p is a plan behavior routine. *An outcome component* q_p is an *n*-tuple $q_p=(q_{p1}, q_{p2}, ...q_{pi}, ...q_{pn})$ where q_{pi} denotes a perception stimulus $q_{pi}=(v_1, v_2, ...v_j, ...v_k)$ that represents the distinctive states of the 3D synthetic world. An SCBR agent receives this perception stimulus as a consequence of a specific previously selected internal action for focusing of attention $f_{qp}=(A_{p1}, A_{p2}, ...A_{pi}, ...A_{pk})$, $i=1,2,...k$.

Here we show an example of a plan case $c_p=(d_p,b_p,q_p)$. Fig. 4 shows an example of a 3D synthetic world. An example of a plan case is $c_p=(d_p,b_p,q_p)$ where:

- $d_p=(R_1, H_1, L_1, H_2, L_2, R_2)$;
- b_p=((exit-from-room, go-to-end-of-hallway, go-right, go-to-end-of-hallway, enter-to-room, go-straight);

Contextual instances for the contextual class '*Room*': R1, R2, R3, R4, R5.

Contextual instances for the contextual class '*Hallway*': H1,H2, H3, H4.

Contextual instances for the contextual class '*L-shaped junction*': L1, L2, L3.

Contextual instances for the contextual class '*T-shaped junction*':T1

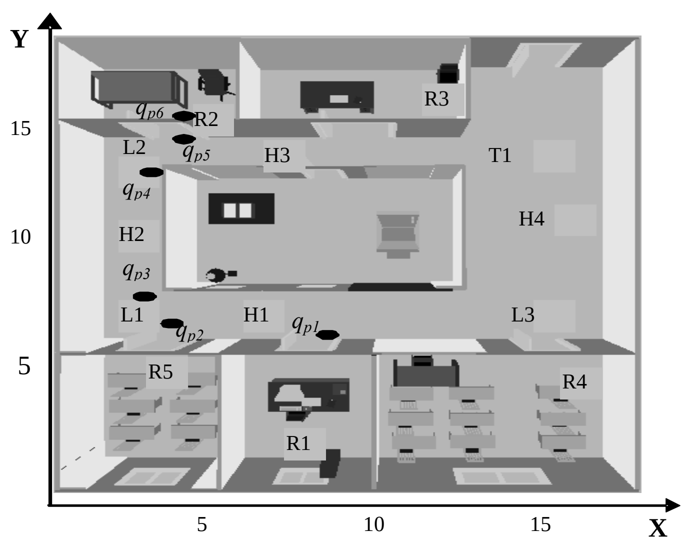

Fig. 4. Example of a 3D synthetic world. The figure shows contextual classes as follows: 'Hallway', 'Room', 'L-shaped junction', 'T-shaped junction'.

- $q_p= (q_{p1}, q_{p2}, q_{p3}, q_{p4}, q_{p5}, q_{p6})$, where q_{p1}=((8, 5.5, 1.57, 5.5), q_{p2}=(4,6,3.14,4.5), q_{p3}=(3,8,1.57,2.8), q_{p4}=(3,12,1.57,6), q_{p5}=(4,14,1.05,2), q_{p6}=(5,17,1.05,2).

Here we assume that the internal action f_{qp} is defined as $f_{qp}=(X,Y, \theta, \Delta S)$ where:

- X,Y and θ denote perception attributes that represent *x*-coordinate, *y*-coordinate and the orientation of an SCBR agent relative to the *X*-axes, respectively;
- ΔS denotes the perception attribute that represents the distance an SCBR agent traversed from one contextual instance to other. For example, the interpretation of the perception stimulus q_{p1}=((8, 5.5, 1.57, 5.5) *is:* $X=8$, $Y=5.5$, $\theta=1.57$, $\Delta S=5.5$.

C. Contextual Cases

A contextual case is a *three*-tuple $c_c=(d_c,b_c,q_c)$ where:

- d_c *is a description component of a contextual case* $d_c=(f, sp_f)$, *where f is an internal action for focusing of attention, and* sp_f *is a perception stimulus that an SCBR agent receives as a consequence of the previously selected action f;*
- b_c *is a contextual behavior routine, and*
- q_c *is an outcome component of a contextual case.*

An outcome component of a contextual case is a perception stimulus that an SCBR agent receives as a consequence of a specific previously selected internal action for focusing of attention $f_{qc}=(A_{c1}, A_{c2}, ...A_{cn})$. Formally, an outcome component of a contextual case is $q_c=(v_1,v_2,...v_i...v_n)$, $v_i \in D_{ci}$, $i=1,2,...n$, where D_{ci} is a domain of a perception attribute A_{ci}.

Here we show an example of a contextual case $c_c=(d_c,b_c,q_c)$. Formal specifications for the contextual case c_c are: $d_c=(f, sp_f)$, $f =(L,R,D,\theta R,\theta L)$, $sp_f =(1,2,\ 2,\ 0.5,\ 0.7)$, b_c=(mrao, md), $q_c =(5,1)$. This example uses the following perception attributes: a distance from an obstacle to a left wall *(L)*, a distance from an obstacle to a right wall *(R)*, a distance from an obstacle *(D)*, an angle to a front-right corner of an obstacle (θR) and an angle to a front-left corner of an obstacle (θL). The solution component b_c contains elements: *mrao (moving-right-to-avoid-obstacle)* and *md (moving-to-door)*. The meaning of the outcome component q_c is determined by internal actions for focusing of attention to the outcome of behavior routines. We will assume the following internal action for focusing of attention $f_{qs}=(\Delta S,\Delta T)$ where ΔS denotes the perception attribute that represents a distance, and ΔT denotes the perception attribute that represents a time interval. The outcome component $q_c=(5,1)$ of the contextual case c_c indicates the traveled distance $\Delta S=5$ by applying behavior routine b_c, and time interval $\Delta T=1$ it takes an SCBR agent to travel the distance ΔS.

Plan cases are used to support reasoning processes at *plan abstraction level*. As a result of reasoning processes at *plan level* an SCBR agent selects an appropriate *plan behavior routine*. On the other side, contextual cases are used to support reasoning processes at *contextual abstraction level*. As a result of reasoning processes at *contextual level*, an SCBR agent selects appropriate *contextual behavior routines*.

IV. An Illustration

To help in understanding how stepwise case-based reasoning model works, we show one situation from autonomous navigation domain. The SCBR agent'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. An SCBR agent selects a current plan intention i_p. Assume that the current plan intention is "*exit-from-room*". This intention directs the SCBR agent's attention to the relevant perception attributes: distance from obstacle to the left wall (*L*) and distance from obstacle to the right wall (*R*). Formally, the SCBR agent selects the contextual action for attentional shift $f=(L, R)$. A perception interface generates the synthetic perception stimulus $sp_f=(1, 2)$. 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 intentions from behavior routines b_c direct the attention to the relevant perception attributes.

Fig. 5 illustrates an example of a navigation task execution. The SCBR agent is here commanded to go from the room $\mathbf{R_1}$ to the room $\mathbf{R_2}$. As the agent navigates this synthetic world, a line is drawn indicating the agent's progress from the start location (S) to the goal location (G). From the example it is obvious that the SCBR agent is successful in carrying out the navigational task.

V. Conclusion and Future Work

This paper describes an approach to the agent's next action selection strategy based on stepwise case-based reasoning (SCBR) at the two abstraction levels: plan abstraction level and contextual abstraction level. The SCBR agent roams in 3D synthetic world based on previous interaction experience and on simulated vision. The SCBR agent's interaction experience is represented in the form of the two types of cases: plan cases and contextual cases. From the behavior of the SCBR agent in the 3D synthetic world it can be concluded that the SCBR approach can be an underlying approach for autonomous agent's action selection strategy. The next step in this line of research should concentrate on developing an appropriate indexing scheme for efficient case retrieval from the SCBR agent's casebase.

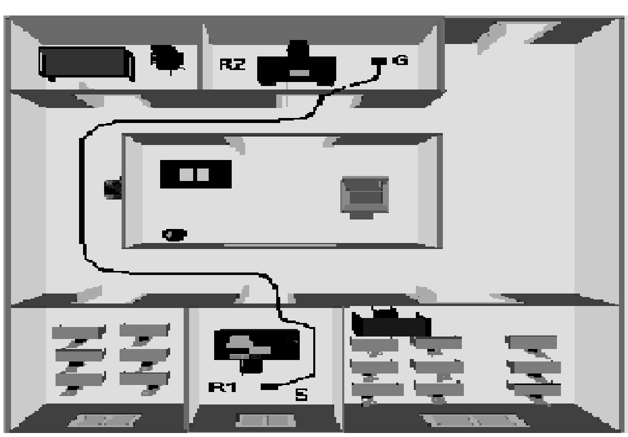

Fig. 5. An example of navigation task execution

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