A Study of Episodic Memory-Based Learning and Narrative Structure for Autobiographic Agents

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Abstract

In this study we develop and compare the performance of different agent control architectures based on learning through episodic memory for the design of Non-Player Characters (NPCs) in computer games. We focus on the Categorised Long-term Autobiographic Memory (CLTM) architecture, utilising abstracted notions of human autobiographic memory and narrative structure humans apply to their life stories. We also investigate the influence of remembering negative experience on agents' adaptivity. A large and dynamic virtual environment is created to examine different agent control architectures in an Artificial Life and bottom-up fashion. Agents' lifespan is measured in the experiments. Results show that CLTM architecture including remembering negative events can significantly improve the performance of a single autonomous agent surviving in the dynamic environment.

1 Introduction

The design of Non-Player Characters (NPCs) has been a critical issue for many modern computer games since game players' expectations are getting higher and higher. Game developers put huge amount of efforts into computer graphics and animations. An additional alternative focus for enhancing their believability in character-based computer games is intelligence expressed by NPCs' behavioural patterns. Although Finite State Machines and Scripting have been two dominant techniques to craft NPCs' intelligence (Cass, 2002), in recent years researchers have attempted applying various AI learning techniques such as Trial and Error, Imitation, Neural Networks and Genetic Algorithm, to create reasonable and intelligent behaviours for NPCs. Among these techniques, Isla and Blumberg (2002) pointed out that, as a learning mechanism with a great potential, *episodic memory* has been only made explicit use by a few behaviour simulation systems. They also indicated that the advantage of using episodic memory for learning, compared to other mechanisms, is speed. NPCs can form usable hypotheses for making decisions or selecting behaviours to execute in the future, after just one observation of users or other agents.

The theoretical term *autobiographic agents* was first defined by Dautenhahn (1996, page 5): "we define the concept of an autobiographic agent as an embodied agent which dynamically reconstructs its individual 'history' (autobiography) during its life-time.". Nehaniv (1999) further pointed out three areas of temporal historical grounding of for narrative autobiographic agents: 1) recognition of narrative structure, 2) expressing narrative structure and 3) having a narrative structure.

Our work focuses on the above areas by building memory architectures for artificial autonomous agents. We expect that, by having narratively structured autobiographic memory as 'extrasensory' data, the increased temporal horizon may free agents from the rigid perception-action cycle. Therefore, the main issue in this paper is to design and validate the bottom-up narrative structure for autobiographic agents in remembering significant events experienced during their lifetime for adaptation to the dynamic environments.

2 Dynamic Virtual Environment and Agent Embodiment

In order to examine the performance of our agent control architectures and the utility of narrative storytelling features between LTM agents in the future work, we required a rich set of possible event sequences. We created a large, dynamic and complex 'nature-like' virtual environment has been created by using VRML and Java programming languages. This environment is fairly different from other simple and flat agent test-beds since it has various types of resources, most of them dynamically distributed on different kinds of

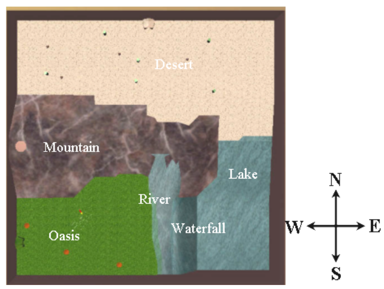

Figure 1: The dynamic virtual environment.

landforms. Figure 1 illustrates the virtual environment model.

All virtual agents are designed to have a finite lifespan and are required to wander in the environment as their basic behaviour. The survival of an agent depends on maintaining homeostasis for its four internal physiological variables, namely *glucose*, *moisture*, *energy* and *body temperature*.

Due to space constraintof this paper, details about environmental structure and agent embodiment in this study can be found in Ho et al. (2005).

3 CLTM Control Architecture

We aim to develop appropriate autobiographic memory architectures on top of a basic subsumption control architecture in order to enhance the agents' performance in surviving in a dynamic environment. Inspired by human long-term memory (Alba and Hasher, 1983) and autobiographic memory models from related research in psychology (Conway, 1992), we developed a more sophisticated CLTM architecture compared with the Purely Reactive (PR), Short-term Memory (STM) and Long-term Autobiographic Memory (LTM) models used in our previous study (Ho et al., 2005). The CLTM architecture addresses our fundamental research issue in this paper – learning through *significant* episodic information. As humans remember experiences in a way that makes narrative sense, we abstract the important points from Linde's narrative structure (Linde, 1993) to create the underlying mechanism for agents to remember events experienced by themselves.

Linde (1993) formally developed a narrative structure for applying to life stories of humans. This narrative structure provides a clear picture regarding different features of narrative and how these features can fit together in a simple personal experience. It can be interpreted as in Table 2 together with how we implement these features into our CLTM architecture:

Feature	Abstract	Orientation (optional)	Narrative	Evaluation
Explanation from Linde	Type of story	Abstractions about who, when, where and what happened	Detailed descriptions of the event(s) that happened in the story	Evaluation of the whole story or a part of the story
Implementation in CLTM architecture	Type of event (which category)	Event abstractions about object area, season, and type (positive or negative	Situations constructed the event (starting, intermediate and ending situations)	Evaluation value (*significance*) of the whole event

Figure 2: Comparison between CLTM architecture and the original explanations for the main features of Linde's narrative structure

Field	Sample Entry
Season	Summer
Object	AppleTree
Landform	Oasis
ChangeOfEngery	– 0.35
ChangeOfMoisture	+ 0.51
ChangeOfGlucose	+ 0.42
ObjectInHand	Stone

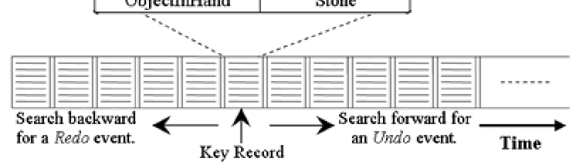

Figure 3: Working Memory consists of situations in CLTM. Events are reconstructed in two directions: *Redo* and *Undo*.

3.1 Working Memory and Event Categories

An CLTM agent surviving in the dynamic environment has a finite list of recent records, called Working Memory; each record is an abstracted situations representing a situation of a particular moment when the agent tries to remember the event context – in this case, the objects and the landform of its surrounding environment and its internal variables. The name of each field in a record and sample entries are shown in Figure 3.

If a record contains a situation when agent was able to sense a resource in the environment, this record will become the *Key Record* for reconstructing events. Starting from a Key Record in Working Memory of CLTM, an agent will reconstruct events experienced in the past in both directions for *Redo* and Undo events. Each event contains an *Evaluation* value which derives from the measurement of the total change of internal variables. The significance of each event is determined by this value. The overall structure of an event reconstructed from Working Memory is similar to Linde's narrative structure.

The second part of CLTM is Event Categories, in which each category contains one type of events. Since the same type of events can be repeatedly experienced by an CLTM agent, only the most significant event (an event with the highest Evaluation value) among repeated events reconstructed from Working Memory is remembered in each category. Categories can be divided into two types: *positive event categories* and *negative event categories*.

3.2 Positive Event and Negative Event

One of the important features of narrative is *breaches* – a story should contain something unexpected, some problem to be resolved or some unusual situation, as described by the founder of narrative psychology Bruner (1991). By considering an event as a narrative which is worth remembering, an event should not only contain general positive information. Therefore we have developed *negative event categories* for CLTM agents to remember negative events which bring negative changes to internal states of them.

In *positive event categories*, an CLTM agent remembers different types of positive event which may guide this agent to locate useful resources in the environment.

Negative events in *negative event categories* can help an CLTM agent to avoid getting into a trouble area which may trap an agent and bring a considerable amount of decrease to internal physiological variables of this agent.

To execute an *LTM Trace* for either a *Redo* or *Undo* event from positive event categories, the agent will try to achieve the next situation from the current situation, until it reaches the target one.

4 Experiments

We aim to measure the performance of three types of agent architectures running in the dynamic virtual environment: Categorised Long-term Autobiographic Memory without remembering negative events (CLTM_Pos); and with remembering negative events (CLTM_Pos_Neg), and Short-term Memory plus CLTM_Pos_Neg (STM+CLTM_Pos_Neg). We carried out 10 experimental runs for each architecture. Each run takes approximately 30 minutes on a Pentium 4 2.0GHz PC with 512MB Ram. For the fifth type STM+CLTM_Pos_Neg control architecture, we have arranged the STM to have higher priority to execute its *Trace-back* process than *CLTM Trace* in the sense of decision making. The starting position for all agents in the experiments is in the center of the oasis area. At the beginning of each experimental run the agent performs a random rotation.

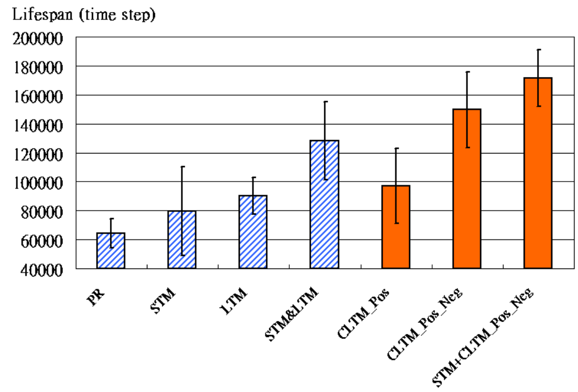

Figure 4: Average lifespan for different types of memory control architectures. Error bars are applied as confidence value to the results. Note that results for architectures PR, STM, LTM and STM+LTM are from our previous work.

In all experimental runs with STM and CLTM architectures involved in, the length of STM is set to 50 entries, and the length of Working Memory in CLTM is set to 30 entries.

4.1 Results

Figure 4 shows average lifespan of totally seven types of agents in 10 experimental runs. To make comparison with memory architectures we developed in our previous study, results for architectures PR, STM, LTM and STM+LTM are from Ho et al. (2005). Details of implementation of these two architectures are not described in this paper, but the simulation environment and experimental conditions in this study are exactly the same as we used in Ho et al. (2005).

4.2 Discussion and Analysis

Results for single-agent experiments in this study can be concluded as follows:

1. The average lifespan of the CLTM_Pos_Neg agent and the STM+CLTM_Pos_Neg agent outperform the PR, STM and CLTM_Pos agent. It implies that remembering negative events helps CLTM agents to be more adaptive in the sense of surviving in the dynamic environment, as agents remembering negative event can avoid repeating the same mistakes of going to some disadvantageous areas. CLTM_Pos architecture does not produce good enough result to significantly outperform PR and STM architectures.
2. Although from time to time the STM agent with *Trace-back* process is able to precisely undo all actions of an event and come back to the resource which was encountered previously; the performance of the *Trace-back* process from the STM

agent is sometimes affected by the environmental dynamics, such as the seasonal resource distributions. Therefore the average lifespan of the STM agent, with a high confidence value, cannot be considered as outperforming the PR agent.

3. The agents with STM+CLTM_Pos_Neg have the highest average lifespan. This result is reflected in agents' memory control architecture as it combines the precision offered by the *Trace-back* process from STM and the flexibility of CLTM to cope with the environmental dynamics.

In our previous study (Ho et al., 2005), we used an list with unlimited length as agents' Long-term Autobiographic Memory (LTM). Each time when an LTM agent needs to retrieve a significant event from LTM, it reconstructs a memory schema which contains a certain amount of useful events experienced in the past, and then rank these events by comparing their significances for selecting the most significant one to execute the LTM Trace process. Compared with LTM architecture, Categorized Long-term Autobiographic Memory (CLTM) we developed in this study has the following advantages:

- The most significant event is chosen from the same type of events and stored into a category. On one hand, this approach saves the computational memory space as agents can safely forget repeated and less significant events. On the other hand, agents can improve the performance by spending less time on searching useful events from the permanent Long-term Autobiographic Memory.
- CLTM agents are able to remember negative events. Some areas in the environment are less beneficial to the agents: either the useful resource are located in the corner which is difficult to be reached, or these areas simply do not have any resource. Remembering the negative experiences in the past may enhance agents chance to survive. In addition to avoid entering the disadvantageous areas, agents staying in 'safe' areas increases their chance to encounter resources.

Therefore, the results produced by the memory control architectures LTM and STM+LTM from our previous study (Ho et al., 2005) are generally not as good as CLTM architectures with remembering negative events.

5 Conclusions and Future Work

In this paper, we developed Categorized Long-term Autobiographic Memory (CLTM) architecture for establishing episodic memory- and narrative structure-based learning dedicated to NPCs design in computer games. Next, through enabling CLTM agents to remember their negative experiences, we showed agents' adaptivity is further enhanced, as shown in experimental results.

In the future, we are interested in investigating how the length of STM and Working Memory of CLTM influences agents' performance. We also expect that if CLTM agents can share both positive and negative experiences through story-telling, interesting results can be obtained through experiments and observations. Furthermore, STM and CLTM agents' further potential can be discovered by running them in a gaming environment with input from human players.

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