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Computational memory architectures for autobiographic agents interacting in a complex virtual environment: a working model

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In this paper, we discuss the concept of autobiographic agent and how memory may extend an agent's temporal horizon and increase its adaptability. These concepts are applied to an implementation of a scenario where agents are interacting in a complex virtual artificial life environment. We present computational memory architectures for autobiographic virtual agents that enable agents to retrieve meaningful information from their dynamic memories which increases their adaptation and survival in the environment. The design of the memory architectures, the agents, and the virtual environment are described in detail. Next, a series of experimental studies and their results are presented which show the adaptive advantage of autobiographic memory, i.e. from remembering significant experiences. Also, in a multi-agent scenario where agents can communicate via stories based on their autobiographic memory, it is found that new adaptive behaviours can emerge from an individual's reinterpretation of experiences received from other agents whereby higher communication frequency yields better group performance. An interface is described that visualises the memory contents of an agent. From an observer perspective, the agents' behaviours can be understood as individually structured, and temporally grounded, and, with the communication of experience, can be seen to rely on emergent mixed narrative reconstructions combining the experiences of several agents. This research leads to insights into how bottom-up story-telling and autobiographic reconstruction in autonomous, adaptive agents allow temporally grounded behaviour to emerge. The article concludes with a discussion of possible implications of this research direction for future autobiographic, narrative agents.

Keywords: computational autobiographic memory; embodied virtual agents; adaptive behaviour; narrative

1. Introduction

Humans and some other animals naturally possess sophisticated memory systems to help them to do reasoning, learning and also sharing of information with others. However, it has been a difficult challenge to model the characteristics of such a memory system in the research fields of both artificial intelligence (AI) and artificial life (AL). In the early stages of dynamic memory research in AI, researchers identified close interactions between three important aspects of intelligence: memory, reasoning and learning (Schank 1982). As remembering past events certainly can help an

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animal or a human to learn from experience, for many years, researchers in the fields of biology, AL and psychology have been investigating how memory influences the behaviour of both humans and other animals.

In recent years, the use of temporal sequences of episodic events, in both robotic and virtual agents research, is a growing area. For example, by collecting relevant events stored in episodic memory, an explorative robot is able to reduce its state-estimate computation in the tasks of localising and building a cognitive map in a partially observable office environment (Endo and Arkin 2003; Endo 2007). Also, long-term episodic memory with attributing emotions may help a virtual robot to predict rewards from human users, thus facilitating human–robot interactions in a simple Peekaboo communication task (Ogino, Ooide, Watanabe, and Asada 2007). In developing character-based AI for computer games, one relationship that has yet to be explored thoroughly is the one between learning and explicit memory formation (Isla and Blumberg 2002). Nowadays, only a few behaviour simulation systems have made explicit the use of episodic memory as a learning mechanism, whereby learning refers to individual adaptation processes that occur within an agent's 'brain'. One advantage of using episodic memory for learning, compared to other machine mechanisms such as reinforcement learning, neural networks or genetic algorithms (GA), is speed. For agents to interact in real-time with each other and/or human users, it is clearly advantageous if they can form usable hypotheses (for making decisions or selecting behaviours to execute in the future) after just one observation of users or other agents (Isla and Blumberg 2002).

Autobiographic memory is a specific kind of episodic memory, which in humans develops in childhood (Nelson 1993). *Autobiographic agents* are agents which are embodied and situated in a particular environment (including other agents), and which dynamically reconstruct their individual history (autobiography) during their lifespan, as defined in Dautenhahn (1996). Autobiographic memory is an important ingredient for socially intelligent agents (Dautenhahn 1999). Moreover, it is useful for synthesising agents that can behave adaptively (Nehaniv and Dautenhahn 1998a), and for designing agents that apparently 'have a life' and thus appear believable and acceptable to humans in scenarios involving people who are observing or interacting with the agents (Dautenhahn 1998).

For many decades researchers in psychology, cognitive science and computer science have widely studied Bartlett's schema theories (Bartlett 1932) which outline the representations and encoding processes of human long-term memory (LTM) (Alpha and Hasher 1983). The core components of contemporary schema theories, such as Frames (Minsky 1975), Scripts (Schank and Abelson 1977) and Mental Models (Johnson-Laird 1980) are derived from aspects of this theory. As autobiographic memory in humans is part of long-term episodic memory, in our work, we apply schema theories in designing autobiographic memory for autonomous AL agents. Here, an important feature is *event reconstruction* (ER), which is reflected in the memory processes of selection and abstraction. A selection process specifies that all incoming stimuli are selectively remembered for memory representation, and the abstraction process denotes that the meaning of an event or a message is stored without entirely referring to its original contents (Alpha and Hasher 1983). Conway points out that episodic memory contains sensory-perceptual information abstracted from working memory. The abstract knowledge is relating to specific goals at a given time, e.g. success or failure to achieve a goal (Conway 2002). Abstraction is important in order to avoid remembering every detail of an event (e.g. in terms of an artificial agent, without abstraction it may remember an event including all its sensor readings, internal states etc. that occured during that event).

Note, our work is inspired by work in cognitive science and psychology on schema theory, and we applied such concepts in the implementation of a working memory architecture for autobiographic agents interacting in a complex virtual environment. In order to do so, many design decisions had to be made for the detailed implementation of this architecture and its computational mechanisms. The lack of granularity of description required to directly translate conceptual/theoretical models that are known in the literature to a working model meant that many details had to be 'filled in'. Thus, we do not claim that every detail of the implementation reflects precisely the current state of knowledge on human memory. However, the primary purpose of our research is a synthetic approach, i.e. to develop autobiographic memory architectures for agents in virtual environments.

In this paper, we study autobiographic memory computationally using a complex, dynamic, virtual 'ecological' environment where agents in order to survive need to forage for food. The life span of an agent, or a group of agents, in this environment is taken as an indicator of its/their survival success. Internal, dynamically changing variables of an agent are influenced by specific resources in the environment. Such ecological environments have been used extensively in AL and adaptive behaviour research, e.g. SimWorld (Schentz and Schermerhorn 2002) or MASON (Luke, Balan, Panait, Cioffi-Revilla, and Paus 2003).

Our work on virtual *autonomous agents* follows a definition of autonomy proposed by Franklin and Graesser: 'An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future' (Franklin and Graesser 1996). Specifically, our approach studies *adaptive* autonomous agents that were defined by Maes as follows: 'An agent is called *autonomous* if it operates completely autonomously, i.e. if it decided itself how to relate its sensor data to motor commands in such a way that its goals are attended to successfully. An agent is said to be *adaptive* if it is able to improve over time, i.e. if the agent becomes better at achieving its goals with experience' (Maes 1994).

Adaptation in our research is addressed by extending an agent's *temporal horizon*, a concept that is explained in more detail in the next subsection, followed by a discussion of the literature of approaches to memory and learning in AI (Subsection 1.2). Subsection 1.3 discusses related work. In Subsection 1.4 we summarise previous work by the authors which lay the foundation for the work presented in this paper. This introductory section concludes with a discussion of the research questions underlying our experiments (Subsection 1.5).

1.1. *Histories and algebras of time*

A feature of memory and remembering is that they provide 'extrasensory' meaningful information by which an agent may modulate or guide its immediate or future behaviour (Nehaniv and Dautenhahn 1998a). Nehaniv motivates this concept of *temporal horizon* by citing Heidegger (1972) who 'saw the state of man as being as situated in the Now, being there in the imminence of the Future in relation to the impinging past' (Nehaniv 1999, p. 1). This temporal horizon can allow for planning for future actions and story telling about past or imagined events. The vast temporal horizon means that humans will tend to deal with interaction in a way that makes 'narrative sense'.

Nehaniv and Dautenhahn have also investigated applying global semigroup theory to the design of autobiographic agents (Nehaniv and Dautenhahn 1998b): they stated that structuring historical memories into algebras allows one to construct expressions in 'algebras of time' that can support recording events of fundamental significance to an agent. 'Expansions are systematic treatments of histories in algebras of time: recording histories of various kinds can be used to systematically "expand" algebras of time into larger ones' (Nehaniv, Dautenhahn and Loomes 1999, p. 8); this corresponds to an expansion of the temporal horizon. By using an expansion rather than the original algebra of time, which describes only the moment-to-moment transitions of the system, it is possible to express formal stories or histories.

Artificial life agents may be able to construct historical grounding as their own autobiography to understand both themselves and each other, since telling (part of) a plausible autobiographical story to others is more than showing a plausible sequence of episodic events (Dautenhahn and Nehaniv 1998). It includes the construction of a plausible story based on one's goals, intentions and motivations (Dautenhahn 2003). Narratives for an agent might be considered stories about the self and serve as a basis for memory, and transmission of such a formal narrative to another agent may be meaningful for the second agent and the behaviour and memories of the second agent could potentially be affected by receiving the narrative (Nehaniv 1999). Note therefore that such formal narratives need *not* be represented in anything like human language.

Furthermore, the potential of autobiographic agents to create stories from their own experiences and understand stories from others may enhance the endurance of events remembered in their autobiographic memory. From a developmental psychology perspective, Nelson pointed out that in addition to the function of language, humans sharing memories with other people, which can be seen as narrative storytelling, performs a significant social-cultural function, and these two functions explain why personal autobiographic memories continue to persist during lifetime (Nelson 1993).

In this paper, we explore different temporal horizons of an agent by investigating systematically different memory architectures and studying their impact on an agent's life span.

1.2. *Alternative approaches to memory and learning in AI*

The utilisation of memory in learning mechanisms in AI, such as *reinforcement learning*[1] and *neural networks*,[2] are very different compared with the approach of episodic memory learning in our research. In this paper, we focus on *investigating how significant events in autobiographic memory affect agents' adaptation to the environment as well as narrative story-telling between agents through a highly abstracted and symbolically-grounded approach*. The reasons for this symbolic approach are as follows:

(1) We are not studying the *emergence* of a capacity to represent episodic and autobiographic memory as a primary focus of research, for which e.g. neural networks might be more suitable.
(2) The representation of episodic memories of the agents should be amenable to examination by the experimenters and their relationship to meaningful events for the agent should be accessible.
(3) The architecture should support explicit communication of specific and/or abstracted episodic histories between agents.

Note, neural networks are especially unsuitable for requirements (2) and (3) above. We take an alternative approach to develop narrative autobiographic agents and to visualise their memories. The visualisation of memory contents enables the monitoring of the learning process of memory agents, such as how an agent manipulates past experiences and why a particular event in the memory is retrieved. This feature becomes more advanced when narrative communications take place between agents since story-telling and story-understanding can be observable.

In the field of behaviour-based robotics, Arkin pointed out that, in the context of computational models used to express brain behaviour, schema theory and neural networks are two mainstream forms fully compatible in building behavioural models: 'Schema theory is a higher-level abstraction by which behaviour can be expressed modularly. Neural networks provide a basis for modelling at a finer granularity, where parallel processing occurs at a lower level' (Arkin 1998, p. 41).

Arbib developed a methodology called Schema-Based Design for creating artificial systems, inspired by ethological and neuroscientific empirical evidence (Arbib 1989, 1992). One of the well-known applications of Arbib's schema theory is named *Robot Schemas*. It distinguishes between a) *motor schemas*, prototypical action patterns available to the agent (controlling locomotion, reaching or grasping, etc), and b) *perceptual schemas*, embedded within each motor schema, that process stimuli (and thus provide the environmental information that the agent needs to know for a particular behaviour).

The approach to modelling autobiographic memory taken in this paper, strongly inspired by schema theory, meets all three requirements listed above and is suitable to address the research questions relevant to this work (cf. Section 1.5).

1.3. *Related work*

Earlier approaches in AI tended to represent knowledge in a machine-understandable and symbolically-grounded way for computers to perform efficient searches for problem-solving. More recent work in *Embodied AI* emphasises the interaction between agents and their environments, in which representations of the same object can be very different and lead to different 'meanings' existing in agents' memories. Researchers suggest that these differences in knowledge representation among agents can be negotiated, e.g. via social interaction (Dautenhahn 1996b) and social learning (Steels 2003).

Research in believable virtual agents has utilised cognitive memory models (Norman and Bobrow 1975), e.g. as applied to the study of synthetic vision for autonomous virtual humans (Peters and O'Sullivan 2002). Strategies for memory storage are usually divided into Sensory, Short-term and Long-term memories according to the rehearsal process and the retaining length of time for an item to be remembered. In addition to memory models, modelling other human cognitive processes has also been a popular research direction in developing architectures for IVAs (intelligent virtual agents) in recent years. For example, Rrad (2002) developed a simple but dynamic neural network model to explain personality outcomes for agents. This Virtual Personalities model generates behaviour patterns that fit models of human personality. Also, after psychologists (Dörner and Hille 1995) proposed the 'Psi' theory which integrates cognition, emotion and motivation for human action regulation, several implementations based on the 'Psi' model attempted to replicate human behaviour in complex tasks (Bartl and Dörner 1998, Dörner 2003, Dörner, Gerdes, Mayer, and Misra 2006).

The OCC model (Ortony, Clore, and Collins 1988) is one of the currently most used appraisal models in the IVA research area. For example, Marsella and Gratch (2003) utilised appraisal processes from OCC for believable characters that perform in various applications.[3] They stated that appraisal variables enable agents to characterise the significance of events from the individual's perspective as the interpretation of each event is altered by an agent's own beliefs, desires and intentions, and past events. Note, believability is not relevant to our work since in our AL approach the agents need to survive autonomously in an artificial ecological environment, without the influence of an 'audience'.[4]

Our work on autobiographic memory is related to the field of *Narrative Intelligence*. Sengers suggested the following definition of narrative intelligence for an agent: '. . .that artificial agents can be designed to produce narratively comprehensible behaviour by structuring their visible activity in ways that make it easy for humans to create narrative explanations of them.' (Sengers 2000). Note, that this definition includes the 'observer', trying to make sense of the agent's behaviour. Sengers provides a detailed interpretation and discussion for applying the characteristics of narrative to the design of intelligent agents (Sengers 2000), relating to ideas from the field of narrative psychology which was founded by psychologist Bruner (1991). Here, two features of narrative, *intentionality* and *breaches* are particularly relevant to our research work for developing narrative autobiographic agents.

Sengers pointed out that intentionality is a critical issue since in a narrative, what actually happens is less important than what the characters feel or think about what has happened. It means that when people watch autonomous agents, they are interested in not only what the agent does, but also how the agent's choice was derived. Therefore, she stated that the agent architecture should be organised so that the agent's reasons for behavioural change are explicit and continuously expressed. Breaches in narrative indicate that a story should contain something unexpected, some problem to be resolved, some unusual situation, etc. Sengers interpreted breaches as an enhancement of intentionality making the agent do something unexpected. Regarding autobiographic memory, the key issue is about significant events – routine events that happen every day, or repeatedly, do not matter as much, and can be encrypted by scripts (Schank 1982). Significant events are 'special' (Sengers 2000) or unexpected events, and they have an important impact on the agent's autobiographic memory. From the perspective of a human (or an agent), his 'life story' (Linde 1993) will consist of a narrative including such 'special events' (Bruner 1991). Narratives are not 'worth telling' unless they include the 'unusual', breaches, violations to the script which make a story interesting (Dautenhahn 2003).

Furthermore, in recent decades, research in narrative intelligence aims to develop agents which can have the capacities of grounding (Nehaniv 1999). Concerned with building this kind of narrative agents, the area has investigated various directions including: interactive drama or storytelling (Mateas 1999; Mateas and Stern 2002; Stern 2003; Cavazza, Martin, Charles, Mead, and Marichal 2003; Magerko 2005; Aylett, Figueiredo, Louchart, Dias, and Paiva 2006; Riedl and Stern 2006; Ram, Ontãnón and Mehta 2007), event structures and organisations for storytelling (Meehan 1976; Lebowitz 1985; Pérez y Pérez and Sharples 2001; Riedl 2004; Gervás, Díaz-Agudo, Peinado and Hervás 2005; Nakasone and Ishizuka 2006; Ho, Dias, Figueiredo and Paiva 2007), social and narrative understanding (Cullingford 1981; Moorman and Ram 1993; Datenhahn and Nehaniv 1998; Dautenhahn 2002, 2003; Mueller 2004), autonomous camera agents (Hornung, Lakemeyer, and Trogemann 2003), narrative in virtual environments (Aylett 1999), etc. Researchers have brought forward fruitful ideas to enhance both storytelling abilities and believability of narrative agents interacting with human users.

Note, in this paper we often refer to 'narrative' and 'story'. In common usage these terms are often used as synonyms, and different scientific sources define them differently. However, for the purpose of this article, from an agent-based perspective, we make the following distinctions. We define story as 'a meaningful sequence of events' (as can be represented in memory): thus a story is not a random sequence of events, it needs to convey an idea or topic and captures the particulars of an occurrence of a sequence of events. Narrative is defined as 'a story being told by, perceived by, or remembered (reconstructed) by an agent', thus a narrative requires a story and an agent interpreting this story. The agent's motivations, goals and other internal states, as well as the context of when and where the story is being told, perceived or rememberd, will influence how the story is being (re-)created. 'Narrative story-telling' refers to the specific process of how a story is being told by an agent.

Developing in a bottom-up fashion computational memory architectures for narrative autobiographic agents inhabiting a complex virtual AL environment is essentially different from many AI approaches to memory, e.g. it fundamentally differs from AI expert systems which usually contain a sophisticated database and apply techniques like Case-Based Reasoning (Kolodner 1993) for tackling problems by remembering new cases, reasoning and retrieving appropriate cases in the specific domain. Regarding knowledge representation, the main issue in this paper is to design and verify the capabilities of autobiographic agents in a) remembering *significant events* experienced during their lifetime for adaptation to dynamic environments, and b) studying the *emergence* of a bottom-up *narrative structure* used in understanding,[5] reconstructing, and telling stories to other agents in a multi-agent context. Thus, the emphasis on our work is on a bottom-up approach towards symbolically grounded, but nevertheless dynamically changing autobiographic memory.

The work presented in this paper is built upon our previous work described in other publications. However, in order to better understand the current work, the next section briefly summarises the main findings of our previous work.

1.4. *Previous work*

Ho, Dautenhahn, and Nehaniv (2003) used a virtual AL scenario consisting of a simple static virtual environment with constant resource distributions and, compared to the current work, simpler memory architectures for very simple, 'minimal', agents. Different control architectures were compared, and the agents' life times were used an an evaluation criterion. Two autobiographic memory architectures, *Trace-back* and *Locality*, were developed, tested and compared to a purely reactive (PR) agent architecture. The agents operated in two different environments. Experimental results confirmed the research hypothesis that autobiographic memory can prove beneficial, resulting in increases in the agents' lifetime. In particular, both Trace-back[6] and Locality[7] autobiographic memory architectures, with or without noise interference, showed superiority over PR control (Ho et al. 2003). These two architectures are shown in Figures 1 and 3.

The way agents encode actions in their memory, with short explanations, are illustrated in Figures 2 and 4. Trace-back is crucial for using autobiographic memory, see Section 3.

We also investigated multiple autobiographic agents able to share an experienced sequence of events (perceptions and actions) with others which have the same goals of wandering and searching for resources so as to survive in the environment (Ho, Dautenhahn, Nehaniv, and te Boekhorst 2004). The results of this study provided experimental evidence to reconfirm that within our framework autobiographic agents effectively extend their lifespan by embedding an Event-based Memory which keeps track of agents' previous action sequences as compared to a PR subsumption control architecture. Multi-agent environmental interference dynamics resulted in a decrease in the agents' average lifespan. Some appropriate combinations of factors, e.g. communication motivation and cost factors, resulted in improved performance.

More sophisticated autobiographic memory control architectures based on a simplified model of human (LTM) were developed and studied in single agent experiments in Ho, Dautehahn, and Nehaniv (2005b). Through experimental results on agents with different memory control architectures surviving in a dynamic virtual environment, we confirmed that a more sophisticated long-term autobiographic memory control architecture effectively extends a PR agent's lifespan. We also gave examples to show how architectures with LTM can effectively maintain the physiological states in the ideal ranges.

Agent architectures with Categorical Long-term Autobiographic Memory which remember both positive and negative events were developed and investigated in Ho, Dautehahn, and Nehaniv

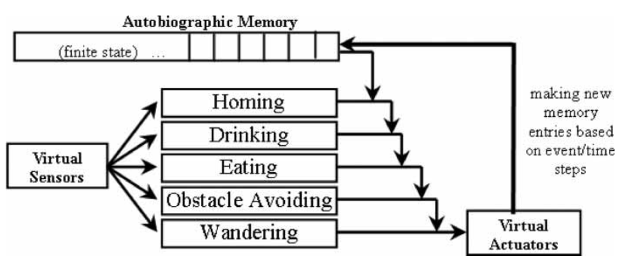


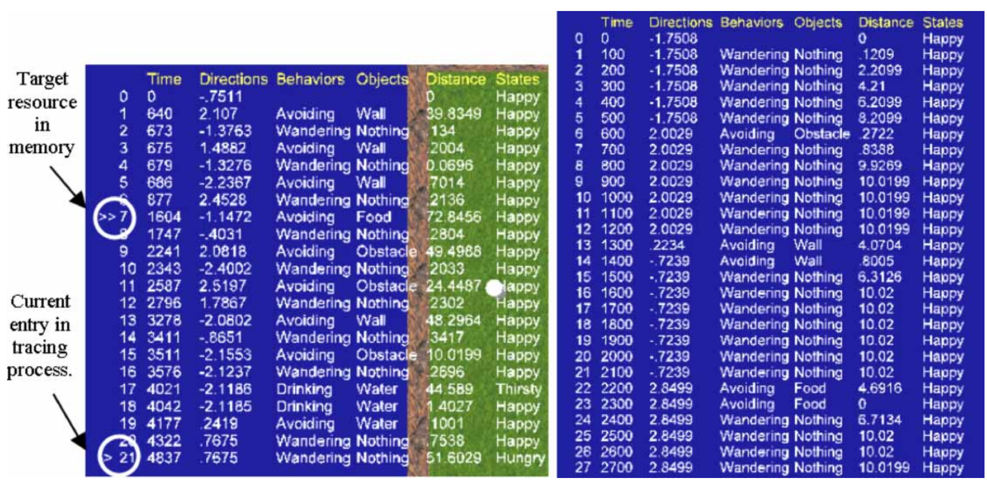
Figure 1. Memory architecture of trace-back mechanism.

(2006). Experimental results showed that it is advantageous for agents (1) to categorise the remembered events for efficient memory retrieval, and (2) to remember various negative events so that they can avoid making the same mistakes again.

In the paradigm of developing synthetic agent architectures, Ho and Watson (2006) proposed that (1) knowledge representations in the computational autobiographic memory can be based on general episodes that agents have experienced, and (2) goal structure, emotion and attention processes, support and are influenced by autobiographic knowledge. Autobiographic knowledge may also support long-term development and learning in synthetic agents as they gain new experience from acting in each new situation. Therefore, character-based narrative story-telling systems can benefit from agents with autobiographic memory.

This paper extends our previous work in Ho et al. (2005b) in several ways:

(1) The new large-scale, dynamic virtual environment can produce complex temporal dynamics involving *irreversibility* (events in the environment cannot be reversed) and *non-commutativity* (changing the order of events will influence the outcome).
(2) We develop a more complex autobiographic memory architecture that combines Short-term Memory (STM) and LTM.
(3) We carry out a series of experimental studies and a quantitative analysis for different memory architectures in terms of how well they are able to maintain an agent's physiological states in the ideal ranges when agents are coping with dynamic environmental conditions in a large-scale virtual environment.
(4) We investigate a multi-agent scenario with narrative storytelling and story-understanding features utilised by groups of autobiographic agents.
(5) In order to visually represent agents' memory contents, we develop the 'observer interface' (see Appendix A). This feature is not only valuable for debugging purposes, but, more importantly, visualises and thus helps understanding of an agent's dynamic memory contents from the perspective of an observer/experimenter.



	Time	Directions	Behaviors	Objects	Distance	States
0	0	-.7511			0	Happy
1	640	2.107	Avoiding	Wall	39.8349	Happy
2	673	-1.3763	Wandering	Nothing	.134	Happy
3	675	1.4882	Avoiding	Wall	.2004	Happy
4	679	-1.3276	Wandering	Nothing	0.0696	Happy
5	686	-2.2367	Avoiding	Wall	.7014	Happy
6	877	2.4528	Wandering	Nothing	.2136	Happy
>>7	1604	-1.1472	Avoiding	Food	72.8456	Happy
8	1747	-.4031	Wandering	Nothing	.2804	Happy
9	2241	2.0818	Avoiding	Obstacle	49.4988	Happy
10	2343	-2.4002	Wandering	Nothing	.2033	Happy
11	2587	2.5197	Avoiding	Obstacle	24.4487	Happy
12	2796	1.7867	Wandering	Nothing	.2302	Happy
13	3278	-2.0802	Avoiding	Wall	48.2964	Happy
14	3411	-.8651	Wandering	Nothing	.3417	Happy
15	3511	-2.1553	Avoiding	Obstacle	10.0199	Happy
16	3576	-2.1237	Wandering	Nothing	.2696	Happy
17	4021	-2.1186	Drinking	Water	44.589	Thirsty
18	4042	-2.1185	Drinking	Water	1.4027	Happy
19	4177	.2419	Avoiding	Water	.1001	Happy
20	4322	.7675	Wandering	Nothing	.7538	Happy
> 21	4837	.7675	Wandering	Nothing	51.6029	Hungry

	Time	Directions	Behaviors	Objects	Distance	States
0	0	-1.7508			0	Happy
1	100	-1.7508	Wandering	Nothing	.1209	Happy
2	200	-1.7508	Wandering	Nothing	2.2099	Happy
3	300	-1.7508	Wandering	Nothing	4.21	Happy
4	400	-1.7508	Wandering	Nothing	6.2099	Happy
5	500	-1.7508	Wandering	Nothing	8.2099	Happy
6	600	2.0029	Avoiding	Obstacle	.2722	Happy
7	700	2.0029	Wandering	Nothing	.8388	Happy
8	800	2.0029	Wandering	Nothing	9.9269	Happy
9	900	2.0029	Wandering	Nothing	10.0199	Happy
10	1000	2.0029	Wandering	Nothing	10.0199	Happy
11	1100	2.0029	Wandering	Nothing	10.0199	Happy
12	1200	2.0029	Wandering	Nothing	10.0199	Happy
13	1300	.2234	Avoiding	Wall	4.0704	Happy
14	1400	-.7239	Avoiding	Wall	.8005	Happy
15	1500	-.7239	Wandering	Nothing	6.3126	Happy
16	1600	-.7239	Wandering	Nothing	10.02	Happy
17	1700	-.7239	Wandering	Nothing	10.02	Happy
18	1800	-.7239	Wandering	Nothing	10.02	Happy
19	1900	-.7239	Wandering	Nothing	10.02	Happy
20	2000	-.7239	Wandering	Nothing	10.02	Happy
21	2100	-.7239	Wandering	Nothing	10.02	Happy
22	2200	2.8499	Avoiding	Food	4.6916	Happy
23	2300	2.8499	Avoiding	Food	0	Happy
24	2400	2.8499	Wandering	Nothing	6.7134	Happy
25	2500	2.8499	Wandering	Nothing	10.02	Happy
26	2600	2.8499	Wandering	Nothing	10.02	Happy
27	2700	2.8499	Wandering	Nothing	10.0199	Happy

Figure 2. Trace-back memory entries made by executing *Event-based* mode (left) and *Time-based* mode (right). The left figure shows a situation when the agent is Hungry (the last column State of current entry) and is starting the Trace-back process since the resource Food was found in its memory (the fifth column object of entry No.7). It will successively undo its actions leading back toward the situation in entry 7. The right figure is similar, but a time-based memory entry has been made every 100 time steps (see the values under the second column Time).

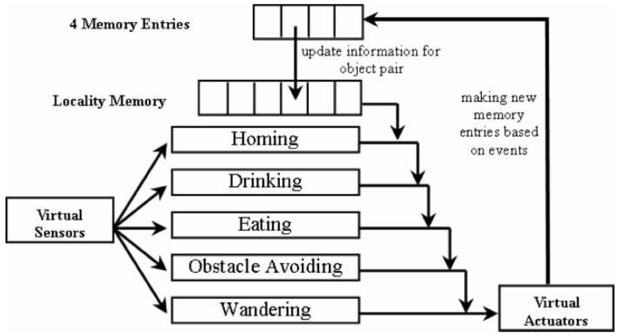


Figure 3. Memory architecture of locality mechanism.

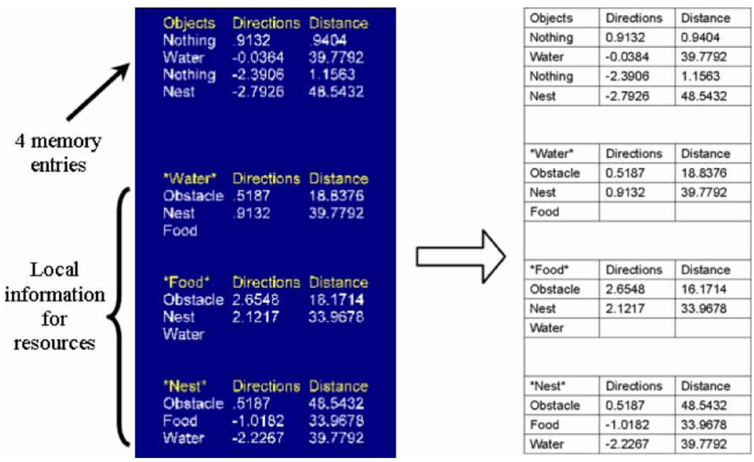


Figure 4. Memory entries made by the locality mechanism. The left figure is captured from a running experiment. For the purpose of illustration, the table on the right represents the same data. Values of direction are shown in VRML rotation unit. In VRML, a π value (3.14159...) is used to represent 180°. For example, if the value of VRML rotation unit is 1.0, this value is equal to approximately 57.30°.

1.5. *Research questions*

In the experimental part of this paper, we address the following research questions:

(1) Does a single agent's survival benefit from short-term and/or long-term autobiographic memory architectures compared to PR control architectures?
(2) Do short-term and/or long-term autobiographic memory architectures increase the homeostasis of agents' internal variables (keeping variables within an acceptable range)?
(3) Does the survival of a group of autobiographic agents benefit from 'narrative communication' which allows agents to share and learn from others' experiences?

Regarding the first research question we expect that, generally, memory will be beneficial for the survival of the virtual agents. We also expect that autobiographic memory with short and LTM will provide extra benefits both in terms of survival and abilities to regulate internal variables, since it allows the agents to deal with different temporal horizons. We also expect that sharing stories in a narrative sense for autobiographic agents can result in better group adaptation in a multi-agent context since it extends the temporal horizon of an agent further and beyond the individual. Thus, we expect that in a group of storytelling AL agents higher lifespans will be observed.

The remainder of this paper is structured as follows. In the following sections we first describe the experimental testbed including virtual agents within a large and complex virtual environment, which dynamically changes its conditions and distribution of resources in order to generate different types of events and temporal sequences of sufficient complexity for the experiments (Section 2). Next we focus on three main agent control architectures (Section 3): PR, STM and LTM. For each of them we illustrate in detail the design concepts of the architecture. For the LTM architecture, we specify its main features, including Event Specific Knowledge (ESK), ER, Event Filtering and Ranking (EFR) processes and particularly aspects for narrative storytelling and story-understanding. This is followed by a section on experiments and analysis of the results (Section 4). Section (5) summarises the main contributions of this work and discuss the potential for future developments. We conclude this article with an outlook on the potential application of our work towards developing software or robotic companions.

2. The virtual environment as an experimental testbed

In order to create rich possibilities of temporal sequences of events for examining the performance of our agent control architectures and the utility of narrative story-telling features between LTM agents, a large, dynamic and complex "ecological" virtual environment has been created using VRML and Java programming languages. This environment is different from other test-beds where the environment is typically two-dimensional with agents moving on a grid, e.g. DomWorld (Hemelrijk 2003), SWARM (Langton, Minar, and Burkhart 1996) or Sugarscape using Starlogo (Epstein and Axtell 1996).

The environment we designed has various types of resources, most of them dynamically distributed in specific areas ('landforms'). Figure 5 shows the design of the environment in an iconic way. Figure 6 illustrates the virtual environment model from two different perspectives. Figure 7 shows metric information characterising this environment.

2.1. *Environment structure*

To create this richness of temporal events, each area in the environment has its unique features, illustrated as follows:

- *Oasis* – this is generally a warm and flat area, which has three *Apple Trees* in the summer.
- *Desert* – a hot and flat area which efficiently provides body heat to the agents and has *Stones* and *Cactuses*. Cactus is the only resource for agents to increase their *moisture* in the winter. To crush the Cactus, agents need to pick up a Stone; this is a realisation of *non-commutativity* (crush, then pick-up is NOT the same as pick-up, then crush), and agents are able to change the Stone distribution in the environment by randomly picking up or putting down the Stone after they have consumed a Cactus.
- *Mountain* – located between the desert and oasis areas; some edible *Mushrooms* exist permanently on top of the mountain, however, climbing up the mountain takes an extra amount of internal energy from the agents.
- *River* – in the summer, it provides water resource to the agents and is located next to the oasis. Agents are able to swim in the river, but they cannot swim towards the north since it is against the current.
- *Lake* and *Waterfall* – these provide another source of moisture and environmental complexity. The waterfall connects to the upper river and the lake. Once agents enter the waterfall area,

they will be picked up by the downstream current and then fall into the lake area. The passage going to the lake area by passing through the river and waterfall areas can be seen as realising *irreversibility*, since an agent is neither able to go back to the river from the waterfall, nor to go back to the waterfall from the lake. Agents have to search for the north exit in the lake area to go to the desert area.

- *Cave* – there are two caves in the environment for agents to regain their energy, one located in the oasis area and the other one located in the desert area.

Two alternating seasons, *Summer* and *Winter*, have been simulated in the environment in order to create a higher level of environmental dynamics (Table 1). Each season has the same duration but different effects on (1) the level of temperature in different areas of the environment, (2) dynamic allocation of resources, and (3) the accessibility of the river.

The temporal richness of events generated by the complex environment particularly includes the following two algebraically non-trivial characteristics (Nehaniv and Dautenhahn 1998b): (1) *non-commutativity* – a sequence of events can be order-dependent, with different effects depending on the specific sequence in which they happen; (2) *irreversibility* – some events cannot be "undone" ("undo" means trying to realise the previously encountered situation by following actions in reverse order).

The system design of the virtual environment can be found in Subsection B.1 in the Appendix.

2.2. *Agent embodiment*

All agents in the dynamic environment are virtually embodied with the same body size and sensors. They are equipped with nine external sensors: seven Hit-Ray sensors (Blaxxum 2004)

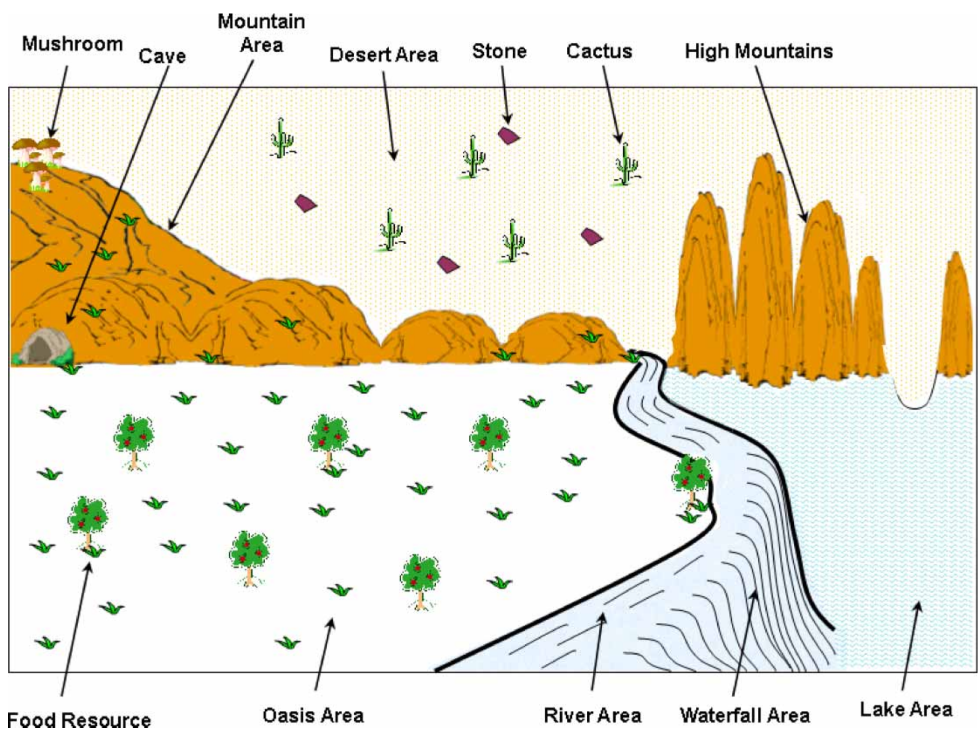


Figure 5. The design of the virtual environment.

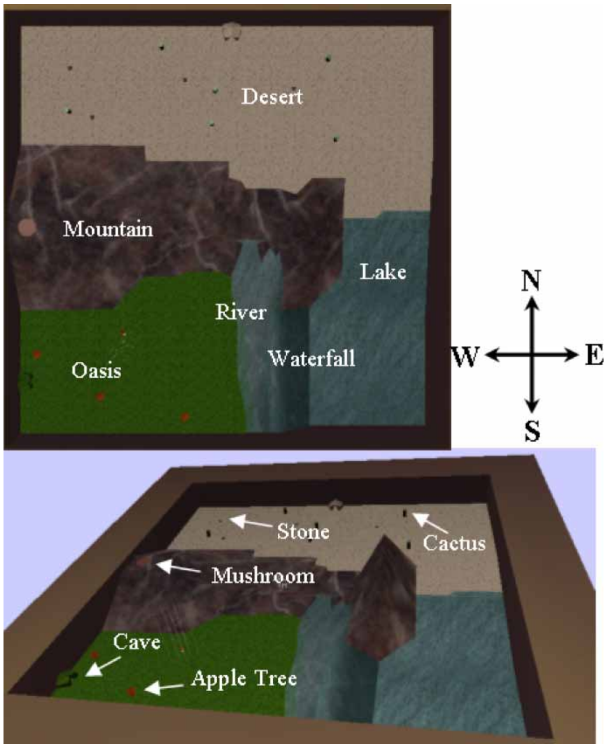


Figure 6. The simulated dynamic virtual environment viewed from two different perspectives. Object locations and landform boundaries are slightly different from the original design shown in Figure 5.

Table 1. Environmental heat, resource allocations and river conditions in the dynamic environment.

	Oasis and mountain	Desert	River, waterfall and lake	Resource allocation	River accessibility
Summer	Cool	Hot	Cool	Oasis – Cave, Apple Tree, River, Waterfall, Lake - Water, Mountain – Mushroom, Desert – Cave, Cactus	Flowing (Agents cannot pass)
Winter	Cool	Warm	Cold	Oasis – Cave, Mountain – Mushroom, Desert – Cave, Cactus	Frozen (Agents can pass)

form a 90 degree fan-shape for detecting the objects, landforms, as well as the environment heat from different types of landforms; the agent body has a landform sensor and also a time sensor for sensing the current season of the environment. Figure 8 shows the distribution of these sensors.

Here we employ the notion of embodiment to our agents as they are *structurally coupled* to their environment. The concept of *structural coupling* originates from ideas (Maturana and Varela 1980, 1987) on the biology of cognition and was later applied to artificial agents (Quick and Dautenhahn 1999). Franklin argued that software systems can be intelligent if they are embodied in the situated sense of being autonomous agents structurally coupled with their environment (Franklin 1997). Thus, in this view the concept of embodiment is not restricted to physically embodied agents such as robots or biological systems.

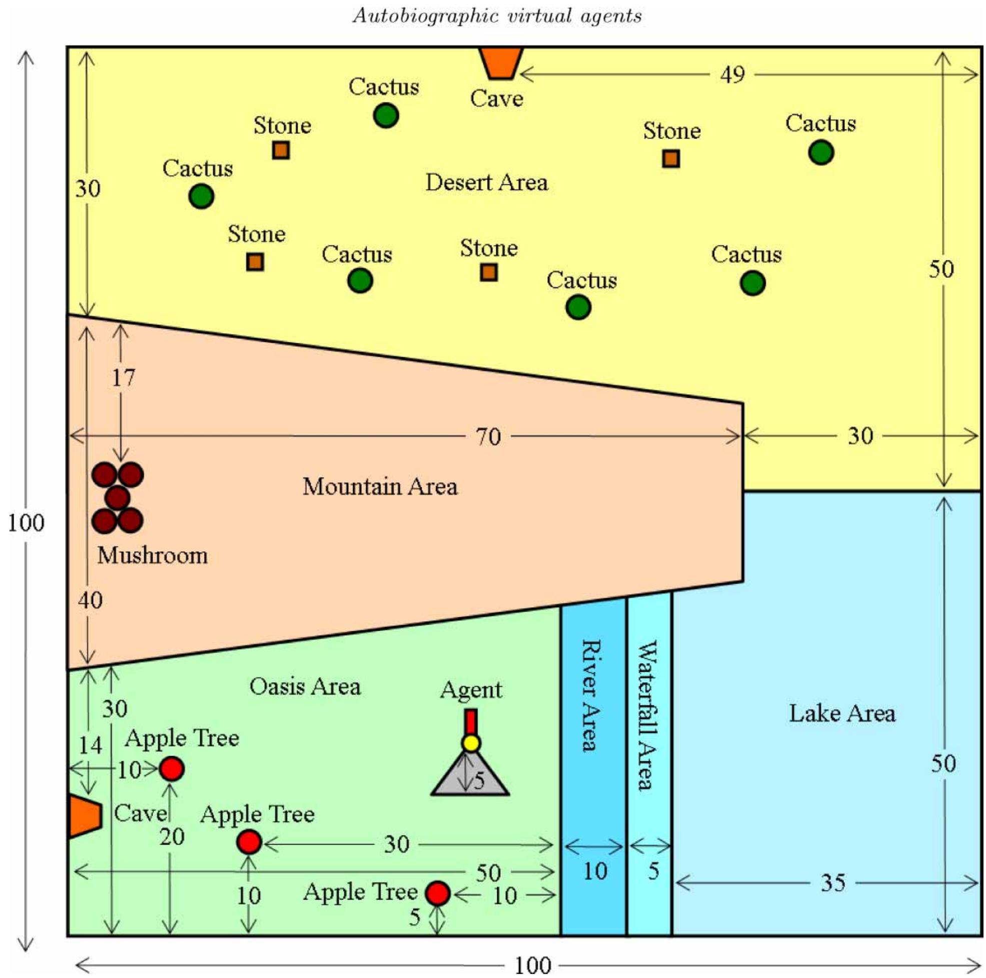


Figure 7. Information represented in VRML distance units for environment size, agents' sensory range and object locations. Note that, for the purpose of visualisation, the actual sizes of the agent's body and resources are smaller in the actual virtual environment. The positions of cactus and stone in the desert area are randomly generated in each experimental run.

We are using internal physiological variables creating a 'synthetic physiology' (Avila-García and Cañamero 2004) whereby an agent's internal variables need to stay within a certain range

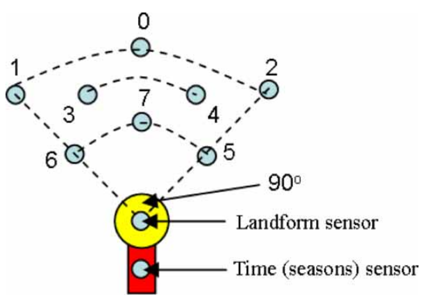


Figure 8. Hit-Ray sensors 0–7 for sensing both objects and landforms, the agent body has a landform sensor and a time sensor.

Table 2. Relationships between agents' internal variables and different resources and contexts in the environment.

Internal variables	Relevant resource (effects)
Glucose	Apple Tree (+100%) Mushroom (+100%) Cactus (+10%)
Moisture	Apple Tree (+100%) Cactus (+10%)
Energy	Cave (+100%) Cactus – touch without stone penalty (−10%)
Body temperature (in each simulation time step)	Desert – Summer (+0.0015%) Desert – Winter (+0.0005%) Oasis – Summer (−0.00025%) Oasis – Winter (−0.0005%) Mountain – Summer (−0.00025%) Mountain – Winter (−0.0005%) Water Area* – Summer (−0.0005%) Water Area* – Winter (−0.0015%) **Water Area = River, Waterfall and Lake*

in order for the agent to survive. All agents are designed to have a finite lifespan and, as their basic behaviour, will wander around in the environment. The survival of an agent depends on maintaining homeostasis for its four internal variables, namely *glucose*, *moisture*, *energy* and *body temperature*. Internal variables *glucose*, *moisture* and *energy* are initialised close to a maximum value at the start of each experimental simulation run and can be increased by taking different types of resources in the environment. The variable *body temperature* is initialised to be acceptable, that is half of the maximum value, and needs to be maintained between maximum and minimum values by regularly wandering in different areas in the environment. Each translation or rotation of the agent will reduce the internal variables *glucose*, *moisture* and *energy* by a certain value. When the internal variables *glucose*, *moisture* and *energy* drop below a threshold, which is half of the maximum value, then the agent begins searching around for resources dynamically located in the environment. When *body temperature* goes beyond the acceptable range – lower than 30% or higher than 70% of the maximum value, the agent needs to move to an appropriate area to regulate *body temperature* until it comes back to the acceptable range again. If the value of one of the internal variables (*glucose*, *moisture* and *energy*) is less than a particular minimum value, or if *body temperature* reaches the minimum or maximum value, then the agent will die. The experimental parameters (thresholds etc.) that allow the agents to live in the virtual environment, but eventually die, were determined in initial experimental tests.

The relationships between internal variables and various types of resources in the environment are shown in Table 2.

The following section describes the control architectures developed and studied in experiments on autobiographic agents.

3. Agent memory control architectures

We aim to develop appropriate autobiographic memory architectures on top of a basic subsumption control architecture in order to (a) enhance the agents' performance in surviving in a dynamic environment, and (b) sharing meaningful information as stories between autobiographic agents. To achieve the first goal, we designed and implemented three different control architectures: PR, STM and LTM. In addition to these three architectures, in the experimental section (Section 4) we also investigate the fourth type, which is built by combining STM and LTM into one architecture in order to broaden the agents' temporal horizon (Nehaniv and Dautenhahn 1998a; Nehaniv 1999; Nehaniv, Polani, Dautenhahn, te Boekhorst, and Cãnamero 2002) (cf. Section 1.1) by taking advantage of more sophisticated memory control algorithms. For both STM and LTM architectures, their distinctive memory layers of control algorithms are built on top of the PR architecture with the aim of inhibiting the execution of behaviour from the PR architecture optionally. In order to carry out the second goal for narrative storytelling between LTM agents (LTM), we established "communication protocols" for storytelling and story-understanding features between LTM agents and enhanced the EFR processes in selecting events to be re-executed among events experienced by the agent itself and told by other agents.

3.1. *Purely reactive architecture (PR)*

In this paper, we define a PR agent as an agent which makes its decisions for executing behaviour solely based on its internal physiological variables and sensory inputs. Therefore we designed and implemented the PR agent by using a basic subsumption control architecture (Brooks 1986), as illustrated in Figure 9. The architecture of the PR agent includes six layers. Higher-level behaviours inhibit or override lower-level behaviours. The agent usually wanders around in the environment by executing the bottom layer in the architecture. When the agent encounters an object, which can be any kind of resource, obstacle or one of the boundaries of the environment (walls), then the agent avoids the obstacle or the wall by generating a random rotation of its body. This behaviour will also be triggered if the agent encounters a resource object and the internal variable which needs that particular resource is higher than the corresponding threshold.

The system design of the PR architecture can be found in Subsection B.2 in the Appendix.

3.2. *Short-term memory architecture (STM)*

On the basis of the design of a PR architecture, STM with memory Trace-back possesses a memory module on top of the subsumption architecture. An STM agent has a dedicated mechanism for making memory entries as the remembering process, and using the memory in a tracing process to attempt to return to required resources. In the case of the Trace-back mechanism, the agent has a finite number of memory entries. Introduction of new entries occurs each time the agent experiences an event, i.e. encounters either an object or agent, enters a new area, or changes its current behaviour. This is called *Event-based* memory entry making mode. Each memory entry includes the current Direction the agent is facing, the kind of Object encountered by the agent (if any), the current Landform the agent now locates on, and how far the agent has travelled (Distance) since the last event. This information is inserted at the current position of the index into the memory table, which has finite length restrained by the current internal variables, but infinite index number. The abstract model of STM is shown in Figure 10.

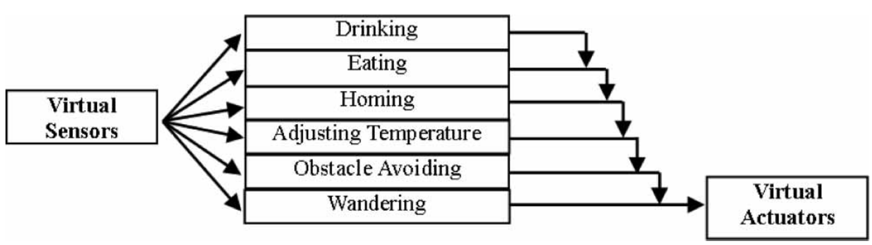


Figure 9. Behaviour hierarchy which is based on the subsumption architecture for a Purely Reactive (PR) agent.

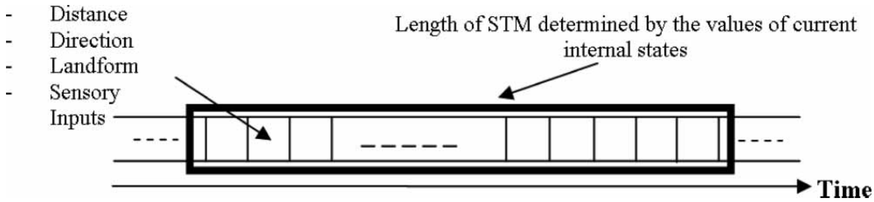


Figure 10. Short-term Memory (STM) with information indicating contents of each entry and the change of its length.

The STM *Trace-back process* will be triggered if one of the internal variables of the agent is lower than the threshold and the table of STM entries has at least one useful entry which indicates that the agent has previously encountered a relevant resource or a landform. Once Trace-back has started, the agents will simply "undo" all previous behaviours. Thus, the agent will execute the reverse of each action step-by-step starting with the most recent action, using the information specified in Direction and Distance. The Trace-back process will be completed once the agent has executed actions undoing all memory entries and has reached the target resource. At this moment, the agent will start sensing around for the resource. During the Trace-back process, we have also introduced noise (Gaussian, standard deviation 5°) to slightly alter the Direction value when the agent is retrieving an entry from its STM. We introduced this noise in order to account for the imperfection of memory retrieval. Therefore, there are possibilities that the resource is not available at this location since (1) some resources in the environment are dynamically distributed; or (2) the actual rotation and distance value in each entry might have been slightly distorted by accumulated errors created by the noise during the Trace-back process. As a consequence of these accumulated errors the agent might not be able to finish the Trace-back process, which is terminated if the agent collides with any other object or agent in the environment.

After an agent performs a Track-back process, the result will be either: target is found or target is not found. In both situations, those undone entries will be cleared and the agent will start making new entries from that point. When an STM agent faces the environmental dynamics, such as unstable resource distributions or the flowing direction of the river and waterfall in summer, these sometimes cause the agent to fail in executing the Trace-back process, whereupon the agent will erase all the memory entries in its STM. An STM agent cannot remember an unlimited number of entries. The number of entries in STM is determined by estimating the costs of executing the Trace-back process of undoing all existing entries. If the cost for one of the internal variables is higher than the current value, then the length of STM will be shrunk by deleting the earliest entries since the agent is not able to afford the cost of doing the Trace back, as illustrated in Figure 10. The processes of erasing undone entries and dynamically shrinking the length of STM can be seen as an improvement from our previous work (Ho et al. 2003,2004).

The system design of the STM architecture can be found in Subsection B.3 in the Appendix.

3.3. *Long-term autobiographic memory (LTM)*

Inspired by human LTM (Alpha and Hasher 1983) and autobiographic memory models from related research in psychology (Conway 1992), we developed a sophisticated LTM architecture, which addresses our fundamental research issue - autobiographic memory. In this LTM architecture, we are interested in investigating how the ER process in LTM can be beneficial when the agent recalls all possible past events from its ESK. Also, we are proposing a method for how an event can be eventually selected from numerous reconstructed events in the filtering and ranking processes.

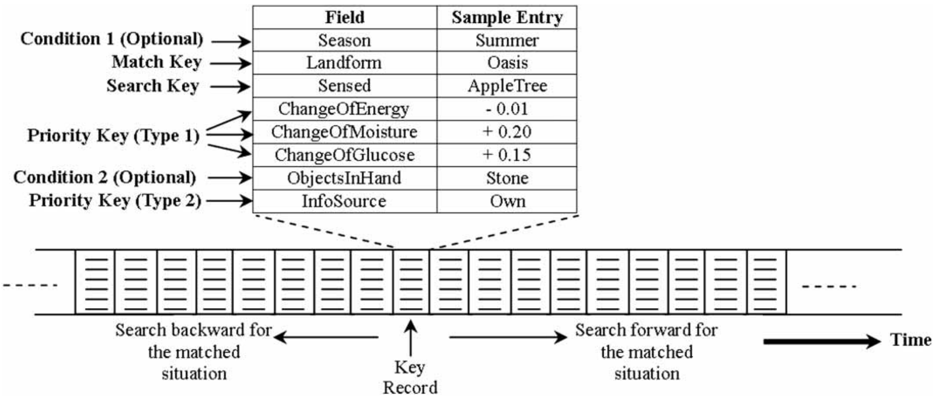


Figure 11. Event Specific Knowledge (ESK) of Long-term Memory (LTM).

3.3.1. *Event specific knowledge (ESK)*

An LTM agent surviving in the dynamic environment has a long list of ‘history’, which contains records of situations, called ESK. Similar to the Event-based memory entry making mode in STM, each record in ESK is 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 physiological variables; the name of each field in a LTM record and sample entries are shown in Figure 11.

Some records, which individually describe special situations about the environment, are noticed by the LTM agent as environmental rules. These records have their unique combinations of various keys: *Condition 1, Condition 2, Match Key* and *Search Key*, where *Search Key* indicates a resource that can be obtained if *Condition 1* and *Condition 2* hold in the area specified by *Match Key*. By recognising and remembering these environmental rules, an LTM agent can enhance the precision when filtering out events in the EFR processes. More details are provided in Subsection 3.3.3.

3.3.2. *Event reconstruction (ER) process*

The ER process proceeds as follows: if one of the internal variables of the LTM agent is lower than the threshold, the agent will search all records in its LTM and retrieve at least one relevant event. In order to form groups of events taking place in different periods of time, and also regarding different types of resources or landform, the ER process retrieves a certain amount of records from ESK and reconstructs each event by using the ‘meaningful’ *Search Key* (Figure 11). Then it will recognise the possible sequence of how an event should be organised - a *Redo* event can be used to repeat a previous situation by executing actions in the original order; in contrast an *Undo* event matches situations that happened in the past which can be reached again by executing inverses of actions in reversed order, i.e. undoing each action.

Deciding the appropriate length of each event, i.e. how many records are related to a specific event, is one of the important processes during the ER process. The *Key Record* (in 12), which can be treated as the agent’s current focus in the ER retrieving process, contains the appropriate *Search Key* to indicate one of the target resources for satisfying the current internal needs of the agent. The length and the final situation of a *Redo* or *Undo* event are recognised by checking the *Match Key* in the *Key Record* to identify the situation that is most appropriate to the current one. Checking the *Match Key* can be done in both directions, searching backward for a *Redo* event

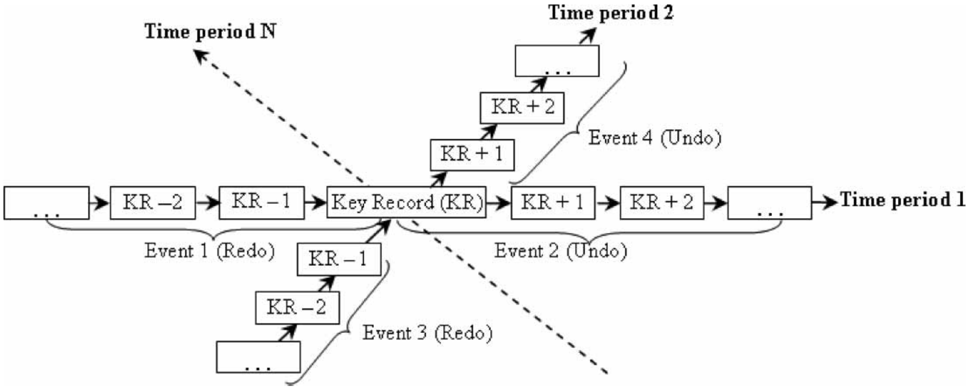


Figure 12. Results from the Event Reconstruction (ER) process – an autobiographic memory schema.

Table 3. Possible events for Long-term Memory (LTM) agent to remember (I: Increase, D: Decrease).

Possible event	Effect to internal variable	Target (resource, object or location)	Environmental condition
Looking for Apple Tree	Glucose(I), Moisture(D)	Apple trees in Oasis area	Summer only
Looking for River	Moisture(I), Temperature(D)	River	Summer only
Looking for Lake	Moisture(I), Temperature(D)	Lake	Summer only
Looking for Caves	Energy(I)	Caves at Mountain's foot	
Looking for Mushrooms	Glucose(I)	Mushrooms	Climbing up Mountains (Energy (D))
Eating Cactus	Glucose(I), Moisture(I)	Cactus in Desert area	With a stone in hand
Hurt by Cactus	Energy(D)	Cactus in Desert area	No stone in hand
Picking Stone	Stone(Picked)	Stone in Desert area	
Location of Mountain area	Temperature(D), Glucose(I) (from Mushroom)	Mountain Area	
Location of Oasis area	Temperature(D), Glucose(I), Moisture(I) (from Apple Tree)	Oasis Area	
Location of Desert area	Temperature(I), Glucose(I), Moisture(I) (from Cactus), Stone (picks up)	Desert Area	
River water flow	Energy(D), Moisture(D), Glucose(D) (gets stuck)	River	Summer only
Irreversible Waterfall	Energy(D), Moisture(D), Glucose(D) (gets stuck)	Waterfall	

and forward for an *Undo* event according to the time. Figure 12 shows, after all possible events have been reconstructed by records from ESK, an autobiographic memory schema dedicated to satisfying a specific internal physiological variable.

With regard to the dynamic virtual environment introduced in Section 2, all possible events which are generated by the environment and can be remembered by the agent in its LTM are classified in Table 3.

3.3.3. *Event filtering and ranking (EFR) processes*

After an LTM agent survives for a certain period of time and wanders around different areas in the environment, its ER process is able to produce groups of events when it needs to retrieve an appropriate event from its LTM. Therefore, in the next stage we add EFR processes to (1) filter out inappropriate events by applying environmental rules learnt from situations when the agent

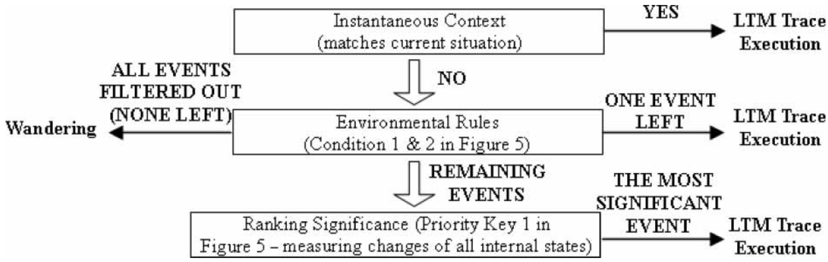


Figure 13. Event Filtering and Ranking (EFR) processes.

was surviving in the dynamic environment, and then (2) rank the remaining events by measuring their significance to the agent. Significance here refers to the positive change to one of the agents' internal states – the larger the change that an event leads to, the more significant this event is to the agent.

The first step of EFR processes is searching for the *instantaneous context*, where the situation the agent is currently facing fully matches the target situation specified by the *Key Record*; in this case, the agent will directly execute the *LTM Trace* behaviour (*Redo*ing a sequence of actions with length zero) and just wander around in the same area and wait for the target object to appear. If the current situation does not match any target situation, in the second step of EFR processes some events which are inappropriate to the current situations will be filtered out by using environmental rules (shown as *Conditions 1 & 2* in Figure 11). If there is more than one event left after the filtering process, a ranking process will choose the most significant event (shown as *Priority Key (Type 1)* in Figure 11) to do the *LTM Trace*. The most significant event is calculated by measuring the total change of internal physiological variables *glucose*, *moisture* and *energy*. EFR processes are illustrated in Figure 13.

To execute a *LTM Trace* (either a *Redo* or *Undo* event), the agent will try to achieve the next situation from the current situation, until it reaches the target. For example, once an LTM agent wandering in the *Oasis* area needs to find *Cactus* in the *Desert* area, this agent follows the reconstructed event experienced in the past, which indicates that in order to reach the desert area, the agent will need to first go to the mountain area, and then to the desert area. Before it can consume the cactus, the event also indicates that the agent should have a *Stone* to crush the *Cactus*; therefore it searches for a *Stone* after it reaches the desert area.

The system design of the Long-term Autobiographic Memory architecture can be found in Subsection B.4 in the Appendix.

3.4. *Narrative storytelling for LTM architecture*

Due to the flexible design offered by the LTM architecture – remembering qualitative situations needed for reconstructing events, we exploratorily defined new 'communication protocols' intended for storytelling between multiple LTM agents. The way communication is established between two LTM agents can be described as 'telling the best story' from the perspective of a story-teller and 'receiving as own experience' from the perspective of a story-receiver. 'Telling the best story' means that, for example, after agent A receives a story request from agent B about finding resources in satisfying at least one internal physiological variable, and if agent A has encountered any related useful resource previously, then agent A will become the story-teller in this case. As a story-teller, agent A then handles this request from agent B as its own demand, so it tries to execute ER and EFR processes – retrieving meaningful information and reconstructing events from ESK, filtering and ranking these events according to the significance of them. If finally

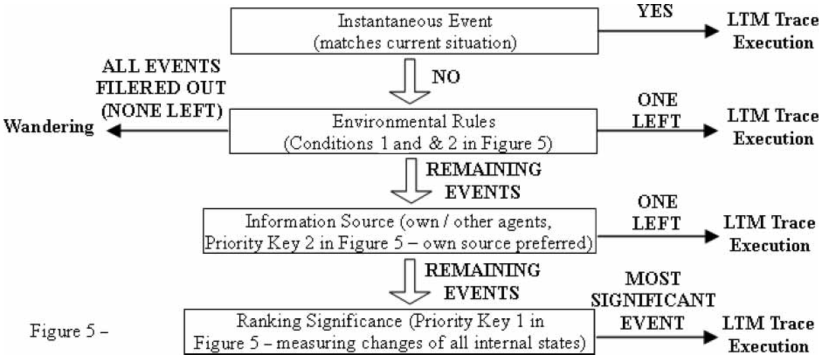


Figure 14. Advanced Event Filtering and Ranking (AEFR) processes for communicative LTM agents.

an event gets successfully generated, agent A will then offer this event as its best story to agent B. Afterwards, as a story receiver, agent B accepts the story reconstructed by a sequence of situations from agent A and remembers it as own experience – regarding this sequence of situations as new situations experienced by itself and stores it in its ESK. Although this sequence of situations is specifically transferred from agent A to agent B and it certainly has useful information for agent B to find out a necessary resource in order to satisfy one or more of agent B's internal variables, it does not have any priority to be recalled later when agent B needs to recall useful information from its LTM.

Note, that this process of 'generating stories to tell' is based on the reconstruction, filtering and ranking of events in an agent's memory. It is not a straight retrieval and transmission of memory entries.

By having the ability to accept other agents' stories, communicative LTM agents now can store not only their own experiences but also others' in their own ESK. While the amount of useful information represented in situations is vastly increased, this in fact creates the additional complexity in selecting which event should finally be re-executed from reconstructed events for *LTM Trace* process. Therefore, EFR processes of communicative LTM agents need to be advanced in order to filter and rank various reconstructed events from different agents. Compared with Figure 13 from the previous subsection, Figure 14 shows the Advanced EFR (AEFR) processes for communicative LTM agents which now, in addition, include an extra process called 'Information Source'. This process selects events completely reconstructed from the agent's own experiences in preference to any events reconstructed from other agents' experiences that may exist in the autobiographic memory schemata generated by the ER process of the agent.

The system design of the Long-term Communicative Autobiographic Memory architecture can be found in Subsection B.6 in the Appendix.

The memory architectures that were described in this section were used in a series of simulation experiments including single-agent as well as multi-agent scenarios. The following section provides details of the experiments and discusses the results.

4. Experiments

4.1. *Single-agent experiments*

To measure the performance of four types of agent architectures, namely PR, STM, LTM and STM + LTM running in the dynamic virtual environment, we carried out 10 experimental runs for each architecture; each run takes approximately 20 minutes on a Pentium 4, 2 GHz PC with 512 MB

Ram. For the fourth type, i.e. the STM + LTM control architecture, we have arranged the STM to have higher priority to execute its *Trace-back* process than *LTM Trace* in the sense of decision making – inspired from autobiographic memory research in psychology (Conway 2005), which indicates that, when processing current goals, humans first form goal-relevant memory contents in their short-term (working) memory and then assume that these memory contents are sufficient, before searching their LTM. The system design of the STM + LTM architecture can be found in Subsection B.5 in the Appendix. The starting position for all agents in the experiments is in the centre of the oasis area. At the beginning of each experimental run the agent performs a random rotation.

Apart from the main measured dependent variable – the average lifespan in 10 experimental runs of each agent control architecture, we also observe and measure the capability of each architecture to keep the agent's internal variables within the acceptable range. Therefore, in each experimental run we recorded the changes of all internal variables over time. We expected that a desirable control architecture for agents surviving in a highly dynamic environment should be able to maintain all internal variables in the acceptable range. In this study, it means that most of the time the internal variables *glucose*, *moisture* and *energy* should be kept at a level higher than a threshold (half of the maximum value).

An agent will expire after 66666 timesteps of life span if it stays in a *non-mountain* (flat area) area and does not perform any action in an experimental run. If an agent is moving continuously in the mountain area, it will have approximately 27000 timesteps of life span. The period of time for each season is 40000 timesteps. The reason for choosing these parameter values is that we aim to allow agents to 'survive' a reasonable length of time, so that they can interact well with the environment and possibly other agents. These figures also apply to experiments with multiple communicative agents in the next Subsection (4.2).

4.1.1. *Results*

Figure 15 shows lifespans with confidence values[8] of four types of agents. Since we are also interested in observing each agent's comprehensive behaviour generated from its unique control

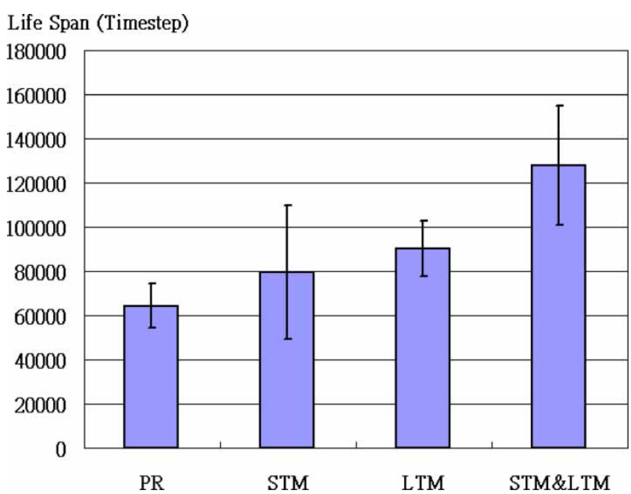


Figure 15. Experimental results with confidence values (error bars) showing the average lifespan of the 4 different agent control architectures: (1) Purely Reactive (PR), (2) Short-term Memory (STM), (3) Long-term Autobiographic Memory (LTM), and (4) Short-term Memory and Long-term Autobiographic Memory (STM + LTM) running 10 times in each condition in the environment. Differences between STM + LTM and both PR and STM are statistically significant, see text for details.

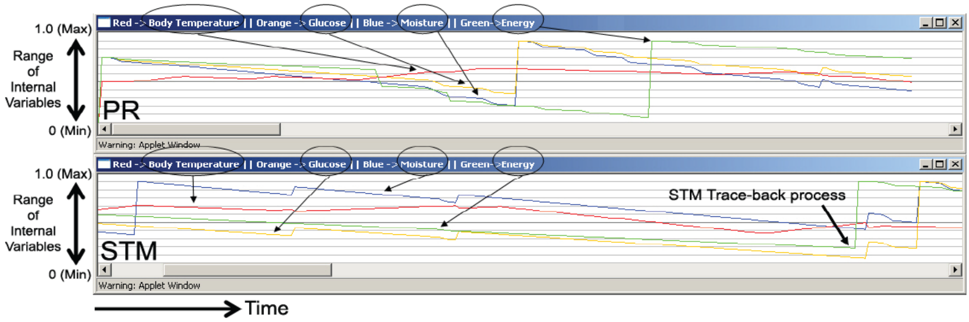


Figure 16. Examples of internal variables' changes of a Purely Reactive (PR) agent (upper graph) and a Short-term Memory (STM) agent (lower graph), in time window of length 25000 steps.

Figure 17. Examples of internal variables' changes of a Long-term Autobiographic Memory (LTM) agent (upper graph) and a Short-term Memory plus Long-term Autobiographic Memory (STM + LTM) agent (lower graph), in time window of length 25000 steps.

architecture, Figures 16 and 17 illustrates, as examples, how well all four types of agents maintain their internal variables. Figure 18 shows a quantitative measurement for each variable indicating the fraction of time staying outside the acceptable range over the whole lifespan for each type of agent – for each variable, the lower the value is, the better the agent is able to maintains its variables within the acceptable range.

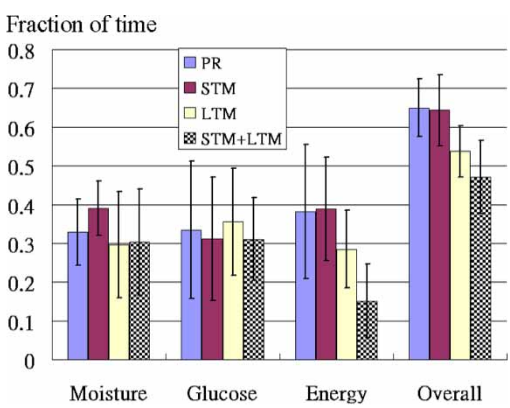


Figure 18. Fraction of time of each variable (*Moisture*, *Glucose* and *Energy*) and overall (any one of them) spent outside the acceptable range over the lifespan for each type of agent control architecture, error bars show confidence values of the results. Differences between STM + LTM and both PR and STM are statistically significant (averaged across all internal variables). See text for details.

4.1.2. *Discussion and analysis*

Figure 15 shows that, at first glance, the average lifespans of the LTM agent and the STM + LTM agent outperform the PR agent, which implies that having LTM helps agents to be more adaptive in the sense of surviving in the highly dynamic environment. However, the performance of the *Trace-back* process from the STM agent is more volatile as it 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. Although, from time to time, the STM agent with *Trace-back* process is able to precisely undo all actions of an event and return to the resource which was encountered previously.

The agents with STM + LTM have the highest average lifespan. A one-way ANOVA showed a main effect for Memory Architecture ($F(3, 36) = 7.582$, $p < 0.001$).[9] Bonferroni post-hoc comparisons show that the STM + LTM agents survive significantly longer than the PR agents ($p < 0.001$) and the STM agents ($p = 0.007$), and marginally longer than the LTM agents ($p = 0.054$). This result is reflected in the agents' memory control architecture as it combines the precision offered by the *Trace-back* process from STM and the flexibility of LTM to cope with the environmental dynamics. Furthermore, agents with LTM appear to be capable of maintaining their variables, except *Body Temperature*, in the acceptable range most of the time, compared to PR and STM agents, as examples show in Figures 16 and 17. In addition to these examples, a quantitative measurement is shown in Figure 18. STM agents need to spend a certain amount of time and energy to execute the *Trace-back* process in order to reach the target resource or landform, as indicated in Figure 16. On the other hand, a two-way ANOVA showed main effects for both Memory Architecture ($F(3, 144) = 5.199$, $p = 0.002$) and (averages across) Internal Variables ($F(3, 144) = 22.762$, $p < 0.001$). Bonferroni post-hoc comparisons show that for STM + LTM agents the internal variables stay significantly longer within the acceptable range compared to the PR agents ($p = 0.005$) and the STM agents ($p = 0.007$). This result indicates that STM + LTM could provide a certain level of 'clues' for agents to search around the relevant areas for resources that are relatively difficult to find in the environment.

Comparing this simulation to the previous work (Ho et al. 2003, 2004), in which we studied a single PR or STM agent surviving in a flat and static virtual environment with constant resource distributions, here results show that LTM agents with a sophisticated autobiographic memory architecture – inspired by human memory research in psychology – can survive and cope with events in a dynamic and temporally rich environment with the characteristics of *irreversibility* and *non-commutativity*. Experimental results and observations showed that the mechanisms for guiding behaviour executions from PR and STM agents tend to be too simple for the dynamically changing environment.

After LTM agents learnt some environmental rules by experiencing them, such as that climbing up the mountain or getting stuck in the lake area will be more detrimental to the levels of its various internal variables than wandering in other areas, they tend to stay wandering in the area where they can find the necessary resource to maintain their internal variables in the acceptable range. The process of ranking event-significance also helps the agent to avoid going to areas highly costly for internal variables.

Finally, compared with STM *Trace-back*, the process of LTM *Trace* keeps the agent's choice open towards all other types of resources. When accidentally sensing other resources, rather than the target one decided by the ER and EFR processes, then the agent will first pick up that resource and then continue the LTM trace, if still necessary, by again executing ER and EF processes to determine its current needs. Moreover, in each fixed period of time, the status of *LTM trace* will be updated in order to (1) cope with target objects which are difficult to find in the area, and (2) switch to other targets for fulfilling the same or a different internal need.

4.2. *Narrative multi-agent experiments*

As defined in Section 1.3, in the context of our AL agents, stories capture the particulars of an occurrence of a sequence of events. Although each agent tries to remember situations and reconstruct events about the environmental conditions from an individually unique perspective, we hypothesise that sharing stories between agents can ultimately produce better utilisation of environmental landmarks for finding the closest resource needed by a specific agent. In this set of experiments with multiple autobiographic agents surviving in the dynamic environment, we investigate the following research questions:

- How can a communicative autobiographic agent perform story-telling and story-understanding?
- Does telling and receiving stories improve the overall performance of agents in a group?
- What kind of story contents can emerge when a communicative autobiographic agent re-organises experiences of its own and other agents? (see detailed observations in Section A in the Appendix)

4.3. *Experimental settings*

To investigate the influences on agents' performance from having a narrative story-telling structure based on a LTM control architecture, we studied the settings shown in Table 4 for multi-agent experiments in the same dynamic virtual environment. The starting position for all agents in the experiments is in the centre of the oasis area. The agents' orientations and positions within that area are randomly chosen but are the same for each run. Due to avoidance behaviour the agents quickly disperse in the area. We measured for each agent individually (a) the story-telling frequencies (including stories told to other agents and stories received from other agents), and (b) the agent's lifespan in each experiment.

Due to the computational constraints, the maximum number of multiple agents surviving in the virtual environment test-bed is five and each experimental run takes approximately two hours in the setting with five agents. As we are particularly interested in studying the emerging narrative story-telling between LTM agents with relatively high communication frequencies, we carried out ten experimental runs for the setting of five communicative LTM agents while other experiments are based on five runs.

4.3.1. *Results*

Figure 19 shows the overall average lifespan for all agents in each experimental setting. Each of the communicative agents' lifespan is shown with the average communication frequency above the result. Both Figure 20 and Figure 21 refer to communicative agents with five agents surviving in the environment. Figure 20 shows results of the agents' average lifespan in each experimental run against the total communication frequency including telling stories to and receiving stories from other agents. Figure 21 shows results of each agent's lifespan in all experimental runs against the story receiving frequency.

Table 4. Experimental settings for measuring narrative story-telling features of multiple LTM agents.

	2 Agents	3 Agents	4 Agents	5 Agents
Non-Communicative	5 Runs	5 Runs	5 Runs	5 Runs
Communicative	5 Runs	5 Runs	5 Runs	10 Runs

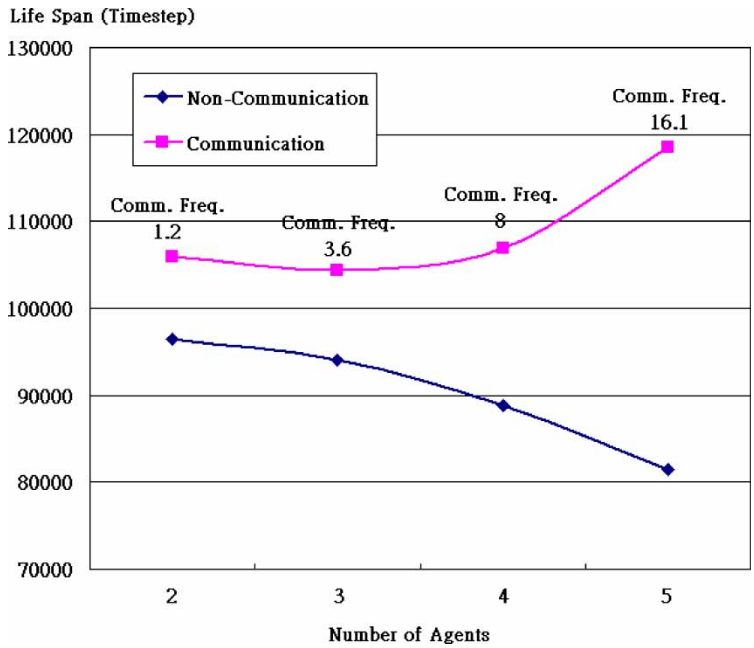


Figure 19. Experimental results of the overall average lifespan for all LTM agents in each experimental setting. The values for average communication frequency are shown on top of the communicative agents' life spans.

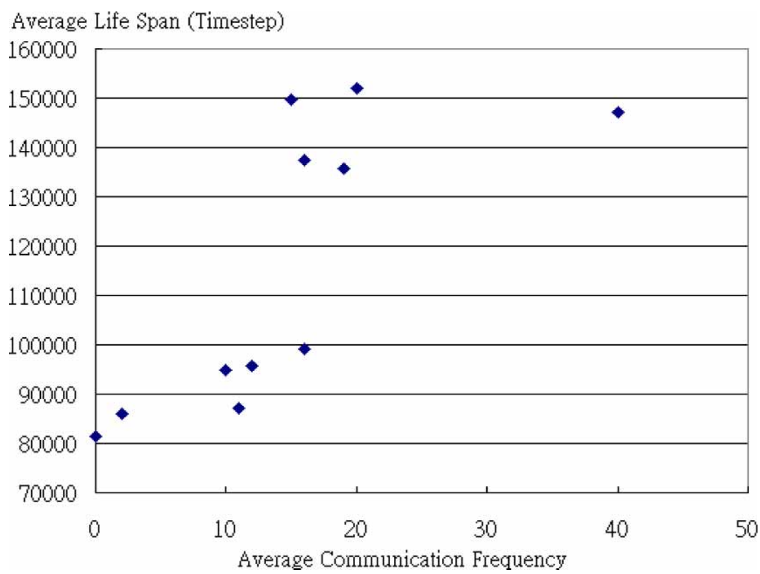


Figure 20. The relationship between average life span and average communication frequency. The correlation between variables was assessed by means of the Pearson Correlation test ($r = 0.678$, $p = 0.031$).

4.3.2. *Discussion and analysis*

Figure 19 shows several interesting results. For non-communicative LTM agents, when more agents are inhabiting the environment, then the average lifespan of these agents is more affected by the extra environmental dynamics created by the agents themselves – many agents running

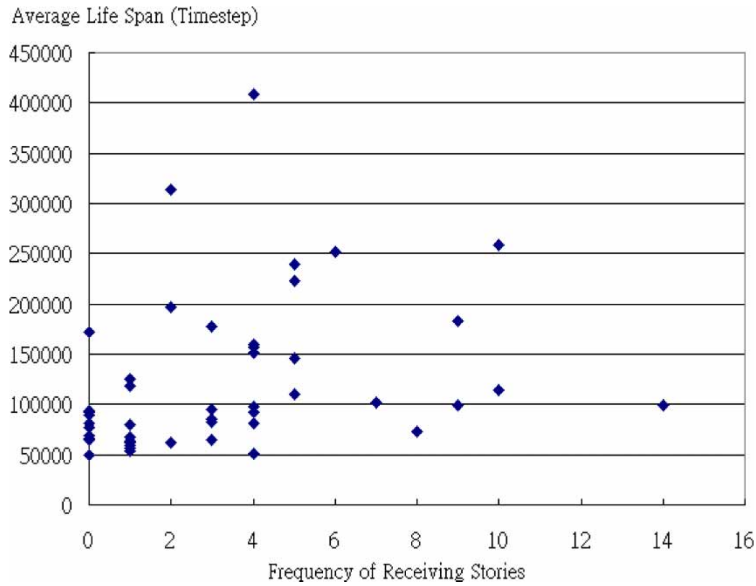


Figure 21. The relationship between each agent's life span and story receiving frequency. The correlation between variables was assessed by means of the Pearson Correlation test ($r = 0.304$, $p = 0.032$).

around tend to disturb one's *Trace-back* process.[10] However, LTM agents with narrative structure are able to cope with this situation by sharing meaningful stories among agents. An exponential-like trend of the increasing communication frequency can be observed when more communicative agents are inhabiting the environment. Particularly, when there are five agents in the environment, then the average lifespan in this experimental setting reaches the highest score of all settings. This establishes that narrative story-telling embedded in the LTM control architecture as an additional communication feature helps agents to be more adaptive in coping with different environmental dynamics.

Focussing on the experimental setting of five communicative LTM agents inhabiting the environment, Figure 20 shows statistically significant results: the average lifespan of communicative LTM agents is correlated with the average communication frequency in each experimental run. The more frequently the agents communicate, the higher their average lifespan, as indicated by the value of Pearson Correlation (r) and the significance of the results (p). We also studied the relationship between event receiving frequency and the lifespan of each communicative LTM agent individually in all experiments; the results are shown in Figure 21. The correlation is weaker compared to Figure 20, but it is positive and statistically significant. The reason is that each individual agent behaved very differently from each other because of the agents' random movements in the dynamic environment. In future work, we may need more sophisticated measurements to further investigate other aspects of this result.

Note that in the experiments involving communicating LTM agents, the communication cost was not set up as one of the parameters in our simulations. In this scenario, communication cost can be introduced as extra time taken from both storytelling and receiving agents for completing their communication. Results are shown in Figures 19, 20 and 21. Modelling communication cost, as we had already done in our previous work with multiple autobiographic agents surviving in a static virtual environment (Ho et al. 2004), is an interesting direction for future research.

The next section briefly summarises the main results and contribution to knowledge of this work. Different avenues for future work are outlined.

5. Conclusions and future work

Story telling and narrative understanding that are characteristic of human (social) cognition are highly challenging tasks in building intelligent agents and have yet to be established fully in AI and other research fields. This research investigated, from a bottom-up perspective, the nature of narrative intelligence for AL agents by making use of stories that are 'natural' and 'meaningful' to them in terms of survival in an ecological, virtual environment.

A series of experimental studies was presented with, where applicable, statistical analysis of the results. With respect to our original research questions and expectations, the experimental results showed that (1) a more sophisticated Long-term Autobiographic Memory control architecture effectively extends the lifespan of an agent compared to a PR or Short-Term control architecture and increases the stability reflected in the changes of internal physiological variables over time; and (2) communicating via narratives helps agents to be able to share significant information and re-organise this information from their own perspective, which counterbalances the extra environmental dynamics generated by multiple agents surviving in the environment. Agents that communicate via narratives have an enhanced lifespan whereby more agent encounters promote a higher frequency of communications.

We have also shown the design of improved STM and LTM control architectures in detail. The combination of them produces the best average lifespan in single-agent experiments coping with dynamic environmental conditions in a large-scale virtual environment. On the other hand, the *System Observer Interface* (see Appendix A) has been developed to illustrate the phenomena of communicative LTM agents completely reusing other agents' stories for finding the necessary resources or partially utilising some significant situations from those stories – an emerging *Mixed Reconstructions* feature.

The current implementation of the OI is rather basic and may be improved to be more interactive and graphically appealing. With regard to user interactions, it may be interesting to allow experimenters to change the contents of agents' memory or to decide which event is more significant to the agent through the interface.

While the results of the simulation studies may not be very surprising as such from a purely Cognitive Science point of view, an important contribution of this paper is the presentation of a working/implemented memory-based narrative architecture for virtual agents in complex scenarios. Such an architecture can be used in future work in a variety of ways, not only for the implementation of virtual agents as part of educational software (Ho et al. 2007), which in fact is our ongoing work, but it could also be used as a testbed for future research into autobiographic memory from a biological/cognitive perspective.

In future, this work can be extended in many ways. First, we can improve the current architecture to get a better coordination of functionalities of STM and LTM; for example, a motivation-based decision making (action-selection) mode, which has preliminarily been studied in Ho, Avila-García, and Nehaniv (2005a), by comparing the performance between Voting-Based, Winner-Take-All and Static-Threshold architectures in a similar virtual environment, may be used to solve the conflicts between the executions of output from STM and LTM. Also, results may be applied to an autobiographic agent society, in which a large number of autobiographic agents can share significant information for completing cooperative tasks.

A certain level of randomness could be added into ESK and the result of reconstructed events for LTM agents in creating the effect of 'forgetting'. In psychology research, forgetting is an important characteristic of human memory that helps humans to learn new tasks and to adapt to new environments quickly. Thus agents' ESK could be redesigned to remember just significant events which have been successfully re-executed, with other events randomly deleted after a certain period of time. However, the side effect of forgetting is that agents will sometimes face incomplete events for the process of *LTM Trace-back* because situations in different events are linked together in sequence; in this circumstance, agents may attempt to repair incomplete events by the enhanced design of (1) ER process – comparing all events internally in order to locate incomplete events and make them traceable; and (2) a 'communication protocol' – resolving incomplete events through accepting and matching events communicated by other agents.

Realisations in artificial agents of story-telling and narrative features can benefit from the increased temporal horizon of autobiographic agents using temporally extended meaningful information (Nehaniv 1999; Nehaniv et al. 2002; Ho et al. 2004). By receiving and re-using (and verifying) stories from other agents, an agent with Long-term Autobiographic Memory may be able to recognise other agents individually. For example, if a narrative autobiographic agent is able to maintain interaction histories and keeps track of the usefulness of stories told by other individuals, then this agent may selectively choose an event from one of its "favorite agents" to execute. This implies that a certain level of trust, as well as distrust, could be built up between agents over time, and thus lay the foundation of the emergence of 'social relationships' between agents.

6. Outlook

> "Instead, today, many AI researchers aim toward programs that will match patterns in memory to decide what to do next. I like to think of this as 'do something sensible' programming. A few researchers – too few, I think – experiment with programs that can learn and reason by analogy. These programs will someday recognize which old experiences in memory are most analogous to new situations, so that they can 'remember' which methods worked best on similar problems in the past." (Minsky 1982, p. 4)

Results presented in this paper are encouraging and we hope to contribute to future generations of narrative and autobiographic agents that have a story 'worth telling' (Bruner 1986). Such autobiographic agents address some of Minky's vision of AI systems that remember past events. What future developments may this direction facilitate?

Autobiographic agents will be useful in many applications where agents 'have a life', i.e. operate for an extended period of time in close interaction with the social and non-social environment. Here, remembering and learning from experience will benefit not only the agent's ability to face new tasks and challenges, but also its ability to relate to users by building and remembering past encounters and take these into consideration during decision-making and action-selection. The ability to remember meaningful experiences with individual users, and the ability to communicate these in a narrative sense, are foundational pre-requisites for robots or software agents that form meaningful relationships with people (Dautenhahn 1998). Such software agents or robots will not only 'have a life', but their 'life' and the way they (inter-) act in the world will reflect their interaction history. Thus, each agent, even when starting with knowledge identical to other agents, will develop its own 'life-story'. This ability will be crucial in application areas where past experience may provide valuable hints to the solution of current problems, as well as areas with repeated and long-term interactions with people. In the latter case, autobiographic and narrative agents will develop and change, alongside their human interaction partners. The way these personalised robot or software companions develop will reflect their social interaction histories and relationships with people (Dautenhahn 2007, 2004). In a certain sense, such AI Systems will mirror the social environment that they are part of: they will be 'more like us'.

Acknowledgements

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Notes

1. Reinforcement learning (Sutton and Barto 1998) is a method by which an agent learns a policy based on a reward (a real valued signal) it receives following the actions it takes. These rewards can be used to teach it any task which can be represented as a Markov Decision Process. In the best known algorithm, Q-learning (Watkins 1989), it builds a look-up table in memory as it explores its environment. This table averages the immediate rewards plus the discounted utility of the successor state for each action in each state. The optimal policy is obtained by taking the greedy action (the action with the highest value) in each state.
2. An artificial neural network is a computational model that is inspired by the brain's information processing ability. It is constructed from a number of units (artificial neurons) which are interconnected by links. Each link has a numeric weight associated with it. Weights are considered as long-term storage in neural networks and learning usually occurs by updating the weights (Russell and Norvig 1994). Artificial single- or multi-layer neural networks are advantageous, especially in pattern recognition and classification tasks. *Recurrent neural networks* (RNNs) take some of the outputs and feed them back to the inputs or to the hidden layer in order to create a dynamic memory, so the networks are responsive to temporal sequences (Elman 1990). In recent years autonomous agents' dynamic properties have been studied extensively. Dynamic neural network models such as *continuous-time* RNNs (CTRNNs) which are used in conjunction with GAs to produce robot controllers, have attracted a substantial amount of interest. An overview of CTRNNs can be found in Beer (1995). Early experiments by using CTRNNs on tasks such as visually-guided orientation, object discrimination and accurate pointing are studied in Beer (1996). Experimental results showed that the internal dynamics allows an agent to make use of the recent history of interaction with the environment for its behaviour execution on simple cognitive tasks.
3. Research on believable agents in AI, inspired by work on believable characters in the Arts, has been pioneered by the Oz project under the guidance of Joe Bates. A believable character is "... one that provides the illusion of life, thus permitting the audience suspension." (Bates 1994, p. 122). Work on believable agents in AI has grown significantly, a complete literature review goes beyond the scope of this paper for which believability of agents as such is not relevant.
4. However, modelling of emotions which are important for believable interactive virtual environments is part of our ongoing research (Ho et al. 2007).
5. Note, we do not claim that our computational agents achieve 'understanding' of stories in a way comparable to human understanding. For the purpose of this paper, 'understanding' of a story by an agent means that the agent is able to remember and reconstruct a sequence of events, relating it to its other previous, past and current experiences. Thus, it refers to a computational, rather than phenomenological notion of understanding.
6. On the basis of the design of a PR architecture, autobiographic agents with memory *Trace-back* or *Locality* possess a memory module on top of the subsumption architecture. Each type of autobiographic agent has a unique mechanism for making memory entries as part of the remembering process, and using the memory as a tracing process. In the case of the *Trace-back* mechanism, the agent has a finite number of circularly-ordered memory entries. The introduction of new entries depends on the way of making memory entries, i.e. either (*Event-based* or *Time-based*). In the *Event-based* mode, making new memory entries occurs when the agent encounters a different object and changes its current behaviour; in the *Time-Based* mode, a new memory entry is made every fixed number of time steps. Information of each memory entry includes the current time step of the simulation, the behaviour which is being executed, the direction the agent is facing, the object encountered by the agent (if any), how far the agent has moved in the environment (distance) since last encountering an object, as well as the current internal variable. This information is inserted at the current position of the index into the finite circular memory. Figure 1 illustrates the memory architecture of the *Trace-back* mechanism, Figure 2 shows examples of memory entries made by executing the *Event-based* mode and the *Time-based* mode.

   The memory trace back process will be triggered if one of the internal variables of the agent is lower than the threshold, and if the corresponding resource can be found at any entry, which indicates that the agent has previously encountered the resource. Once trace back has started, the agent will simply 'undo' all previous behaviours. As indicated in Figure 2, the agent will execute in reverse order the action to undo each step starting from the current entry to the target resource. This mechanism has a close connection to the group-theoretic notion of inverse in mathematics (Nehaniv and Dautenhahn 1998a). Thus, the agent will execute the reverse of each action step-by-step starting with the most recent action, using the information specified in Direction and Distance. The trace back process will be completed once the agent has executed all memories entries and has reached the target resource. At this moment, the agent will start sensing around for the resource. Note, there is a possibility that the resource is not available at this location since the actual rotation value in each entry might have been slightly distorted by noise. Also, the trace back process will be terminated if the agent collides with any objects in the environment (e.g. due to accumulated errors caused by noise).
7. In contrast to the *Trace-back* mechanism, the *Locality* memory agent has only four memory entries for remembering the most recent behaviours using the *Event-based* mechanism. In addition, the agent maintains information relevant for travelling from one type of object to any other type of object (*Locality* memory). Making or replacing entries of long-term *Locality* memory occurs exactly when a particular pair of objects has been encountered. The reason for having four memory entries at the top of architecture (see Figure 3) is as follows:

(1) Each complete action occupies two entries. In the first entry the agent rotates its body to avoid an object; in the second entry it travels in a straight line to depart from that object.
(2) Information showing the relationship between a pair of useful objects contains two contiguous actions.

Three tables represent all relevant information for the possible specific pair of objects; each row of the table contains information of Direction and Distance, specifying what the agent did while travelling between two objects (cf. Figure 4). The tracing memory process occurs when the agent is looking for a specific resource and the entry of the object leading the agent to that resource contains the required information.

8. Confidence value is the mean of standard errors, it shows that 95% of the average of the experimental results can be obtained from the confidence value interval.
9. Although error bars can show the pattern of differences between types of memory, ANOVA (with post-hoc comparisons) was employed in order to discover whether these differences are statistically significant, or simply due to random/chance factors.
10. A similar effect of inter-agent interference has been found in other experiments with groups of robotic agents, e.g. (Beckers, Holland, and Deneubourg 1994).

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Appendix A. Observer Interface (OI)

The OI was designed to essentially focus on how contents of STM and Long-term Autobiographic Memory (LTM) can be illustrated explicitly to human observers. Memory contents, particularly for LTM, are relatively complicated so a representation was chosen that is appealing in depicting agents' memories to experimenters/observers who are trying to understand the dynamics of an agent's autobiographic memory.

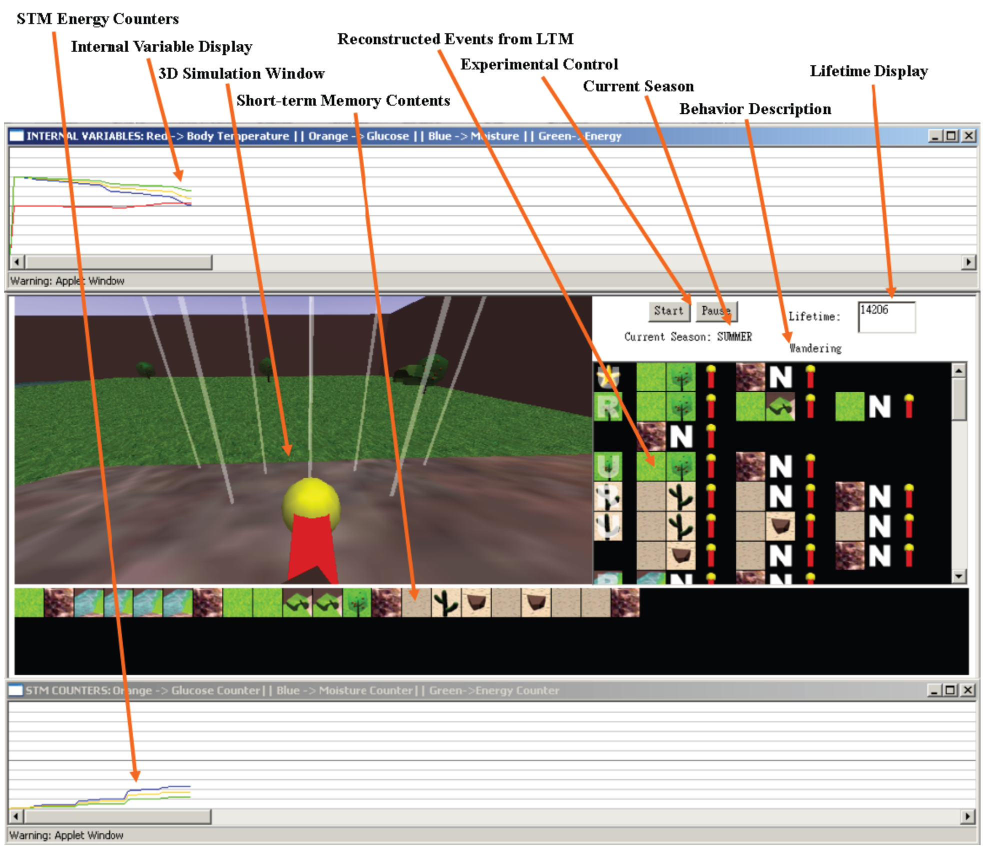

Figure A1. The Observer Interface for STM + LTM agents indicating the main components.

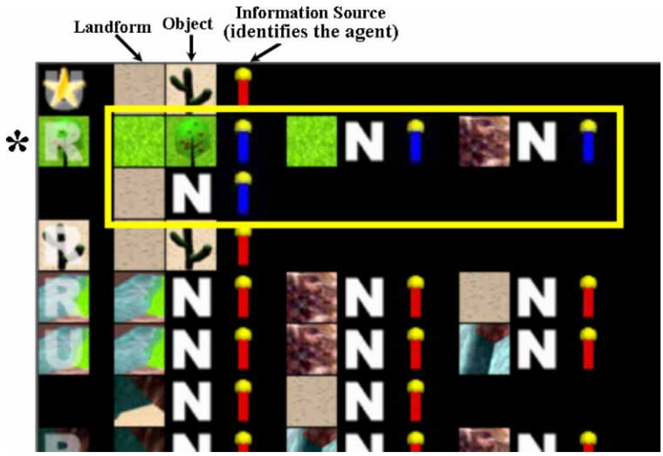

Figure A2. The highlighted area in this figure shows that the agent has reconstructed an event completely from another agent's experience. This is a "Redo" event with an apple tree as the target, as indicated by the letter "R" on the left most apple tree icon (*). Four situations are shown in inverse order and each situation is represented by a triple of icons. Starting with the last triple (*DesertArea-NothingSensed-BlueAgentStory*), it shows that the event was started when the blue agent sensed nothing (symbol "N" in the middle icon) in the desert area. The blue agent then reached the mountain area, depicted by the second last triple (*MountainArea-NothingSensed-BlueAgentStory*). Finally the blue agent arrived in the oasis area (*Oasis-Area-NothingSensed-BlueAgentStory*) and sensed an apple tree (*OasisArea-AppleTreeSensed-BlueAgentStory*). Note that, in this figure, "blue agent" refers to the deep-grey colour agent body in the black and white version of this paper, and the red agent should be shown as light-grey colour in respectively.

Considering the difficulties in representing the rich amount of memory contents from the schemata of autobiographic memory (see Section 3), we adopted the concept of the *meaning triangle* (Sowa 1999) to represent agents' memory contents in a higher level and easily understandable way – using icons. The term *meaning triangle* was popularised by Ogden and Richards, but Aristotle was the first to make the distinction, the history of meaning triangle can be found in Sowa (1999). The meaning triangle shows how humans deal with the relationships between an real object, the concept of that object and the symbol of that object. Therefore, we introduced triples of icons to represent memory objects in the OI as it can be easier for human observers to understand (1) the current memory contents in an agent's LTM and (2) how these memory contents get re-organised dynamically. Although each triple of icons is not able to fully represent the details of a situation, it contains most representative information for an agent to find a target situation in one step.

The system design of the Observer Interface can be found in Section B.7 in the Appendix.

Figure A1 shows the complete OI that was developed for STM + LTM agents. In comparison, the OI for PR agents has no memory contents to display, for STM agents it has only STM contents, and for LTM agents it has only reconstructed events from LTM. The OI offers basic control for experiments (Start and Pause buttons) and indicates the current season

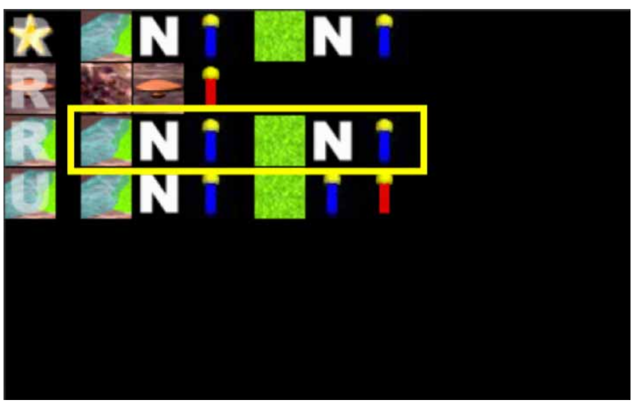

Figure A3. The highlighted area in the figure shows that the agent has reconstructed an event completely from another agent's experience.

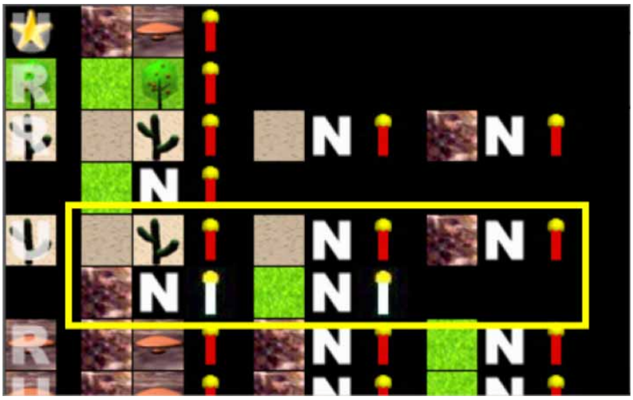

Figure A4. The highlighted area in the figure shows that the agent has reconstructed an event by applying *Mixed Reconstructions* – this event contains situations from the agent's own and another agent's experiences. The experience from another agent can be seen from the *Information Source* with the white color agent body in the last two situation triples.

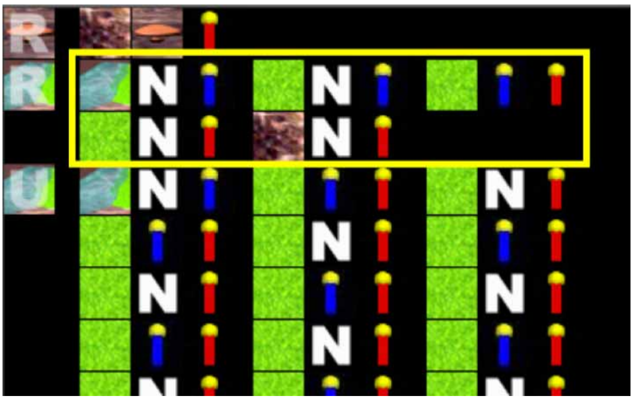

Figure A5. The highlighted area in the figure shows the agent has reconstructed an event by applying *Mixed Reconstructions* – this event contains situations from the agent's own and another agent's experiences.

of the environment and the agent's behaviour and lifetime. In addition to showing the contents of STM and LTM, it also updates an agent's current internal variables and STM energy counters in a representation of lines – showing the trends of these variables over time.

Through the OI, we are also able to observe the details of how narrative story-telling helps agents' survival – the story properties reconstructed in ER process by communicative LTM agents. Reconstructed events from LTM of an individual agent are represented as groups of triple icons in the OI, as shown in Figure A1. Each triple contains *Landform*, *Object* and *Information Source* (identifies the agent). The interface represents the detailed situations of single events, as illustrated in Figures A2 to A5 which are extracted from the screenshots of the complete OI. As an example, a description of an illustrated event is given in Figure A2. We discovered that communicative LTM agents are not only able to completely reuse stories told by other agents (Figures A2 and A3), but they also reconstruct new stories by partly using situations extracted from other agents' stories (we call these *Mixed Reconstructions*, and they are illustrated in Figures A4 and A5). *Mixed Reconstructions* can be seen as an *emerging effect* offered by the narrative story-telling structure and the characteristics of the ER process in reconstructing events. This results in re-organising significant situations to increase the efficiency of the reconstructed events for finding necessary resources in the dynamic environment. Furthermore, after agents survive for a certain period of time and the communication frequency among them increases further, agents' experiences can be further shaped by exchanging the best stories offered by one agent to others.

Appendix B. System design for architectures and environment

In this appendix, we illustrate system design diagrams for the virtual environment and agent control architectures. In order to show the main characteristics of each architecture, descriptions are provided and some important features are highlighted in each diagram. The information provided should allow readers of this article to replicate the agent architecture described in Section 3.

To help understanding the symbols used in each data flow diagram which represents the functional structure of an agent control architecture, Figure B1 shows standard data flow diagram symbols with descriptions.

B.1. *The dynamic virtual environment*

The design of the large and dynamic virtual environment for our studies of single and multiple autobiographic agent experiments is shown in Figure B2. In addition to having various types of object and landform, this environment is relatively large in comparison to the environments used in the early studies. Moreover, environmental heat provided by different types of landforms is constantly changed in each season. River, Waterfall and Lake are special landforms, since they provide also moisture resource (water) to the agent. However, in the winter season water in these three landforms will be frozen and thus the moisture resource will not be available.

There are two types of objects: static and dynamic. The distribution of dynamic objects is different in each season. Stone is a specific kind of dynamic object since it can be collected by the agent and go with the agent until the agent drops it down. A drawing model and screenshots of this environment and the agent design can be found in Section 2.

Figure B3 illustrates the interactions between the Script program which controls an agent's behaviours and the dynamic virtual environment. An agent's movements and communications are controlled by Script programs. However, there is an extra *Environment Script* for controlling the environmental dynamics – objects' distribution and environmental effects, such as fog, lighting and dynamic landforms.

B.2. *PR agent architecture*

Figure B4 illustrates the data flow diagram which represents the structured design of the PR architecture. Since the agent has one more internal state (Body Temperature) to maintain, it has to reach a proper area to adjust Body Temperature when its value exceeds the upper or lower threshold.

B.3. *STM architecture*

Based on the design of PR agent, the STM architecture has one improved feature compared with *Trace-back* architectures from the early studies – *Energy Counter* which dynamically shrinks the size of the memory according to the energy counter values. Figure B5 illustrates the data flow diagram which represents the structured design of the STM architecture. Environmental rules can be learnt if an STM agent has experienced an irreversible event. These rules can help the agent to validate memory entries which do not violate any rules learnt. For the data structure of STM, see Figure 10 in Section 3.

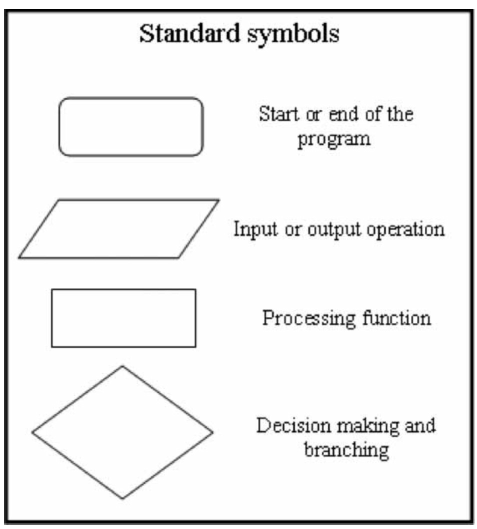

Figure B1. Standard symbols used for creating the data flow diagram in this appendix.

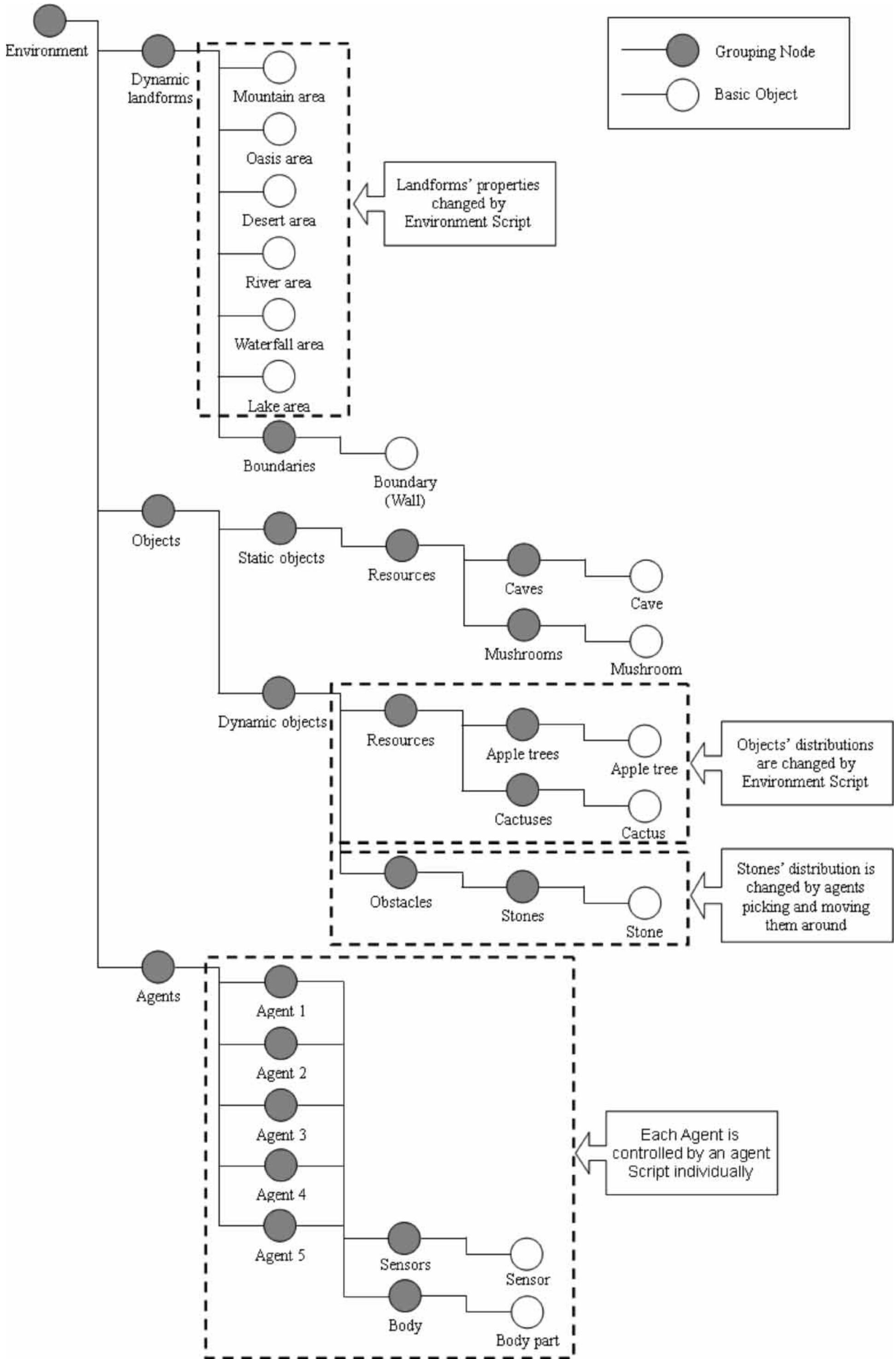

Figure B2. System design of the large and dynamic virtual environment for single and multiple autobiographic agent experiments. Nodes relating to environmental lighting and user viewpoints are omitted in the figure.

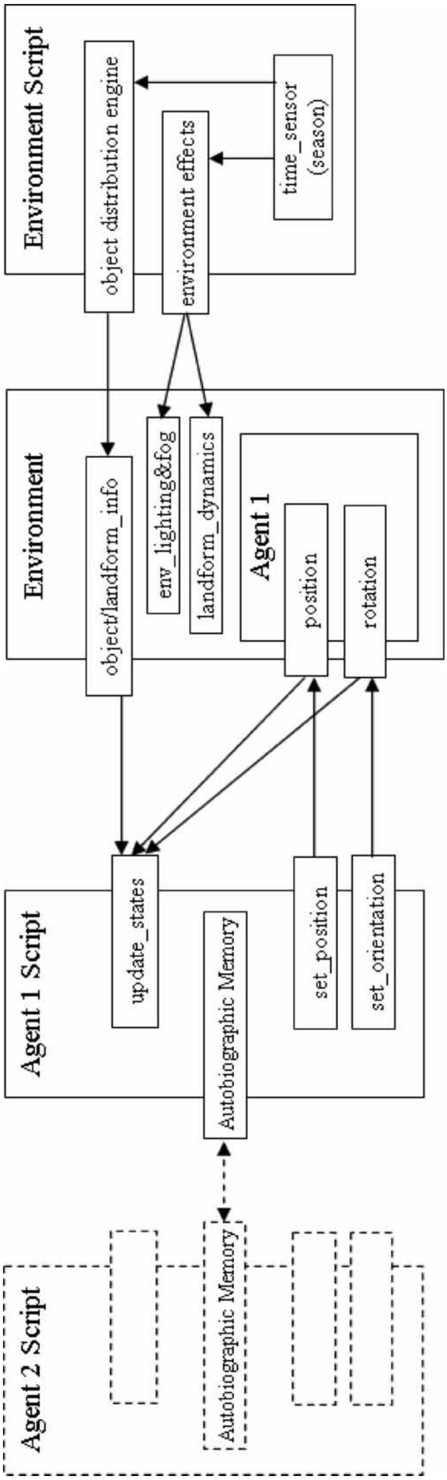

Figure B3. Interactions between the Script program which controls an agent's behaviours and the dynamic virtual environment.

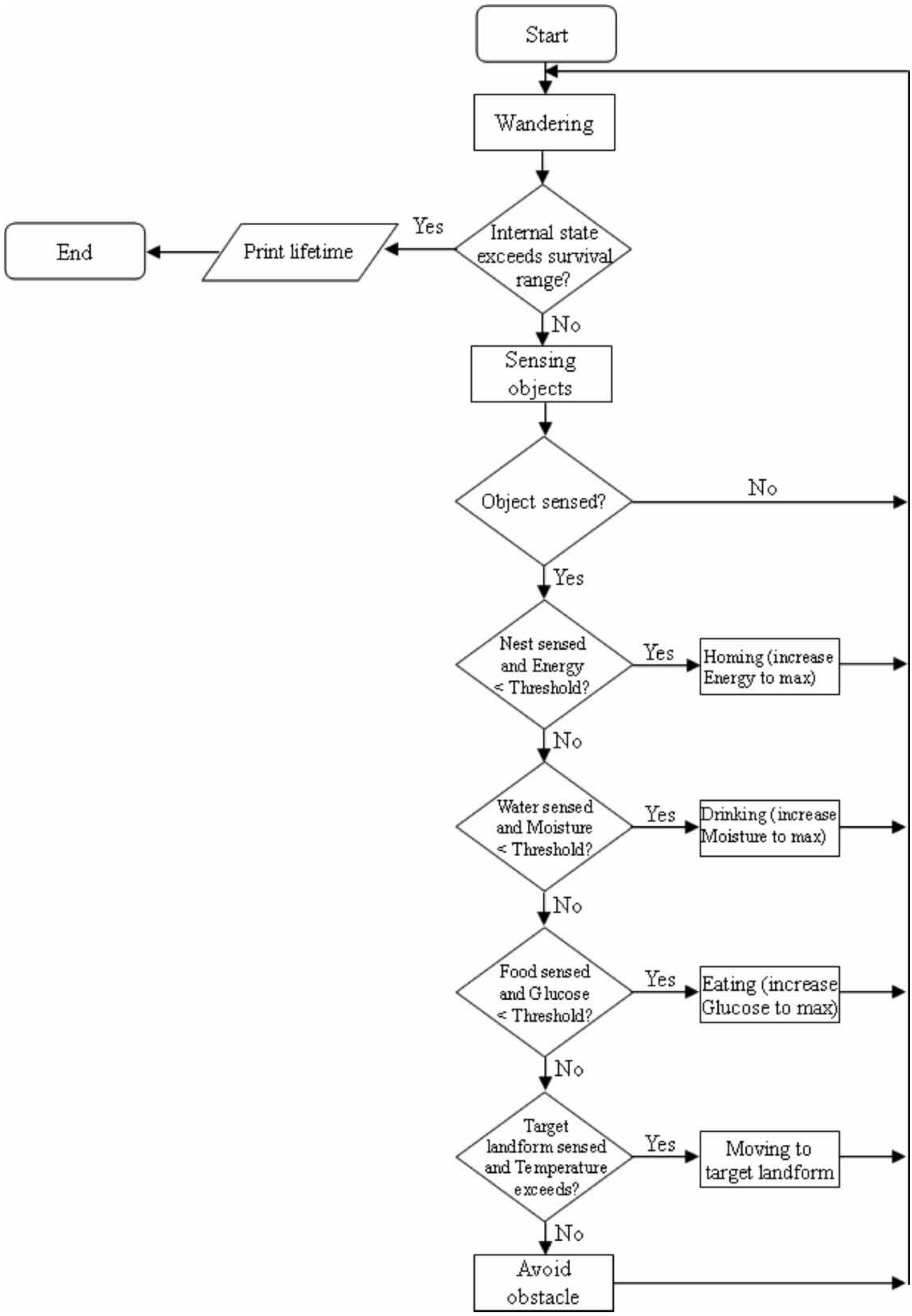

Figure B4. Data flow diagram of the Purely Reactive agent architecture.

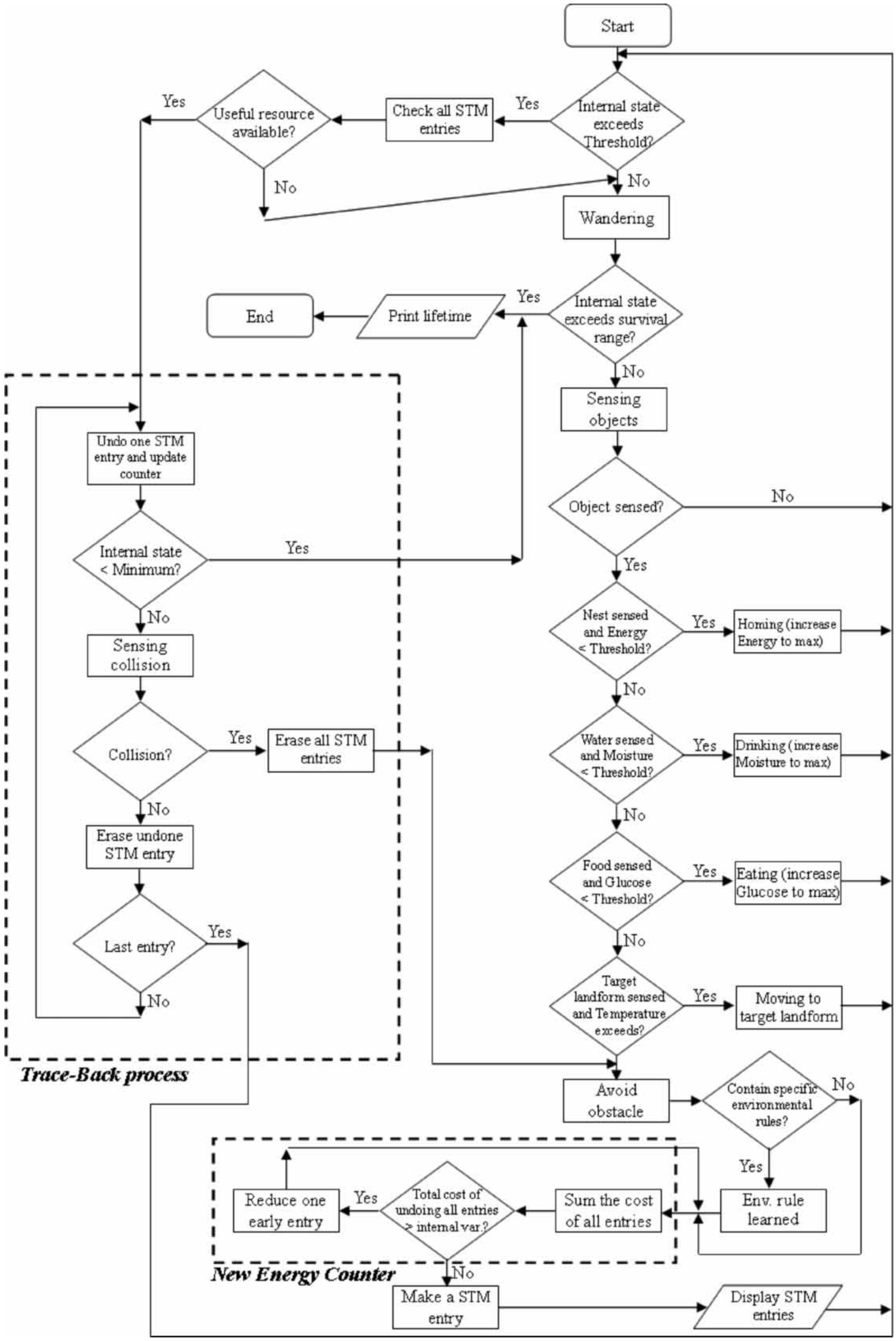

Figure B5. Data flow diagram of the Short-term Memory (STM) architecture.

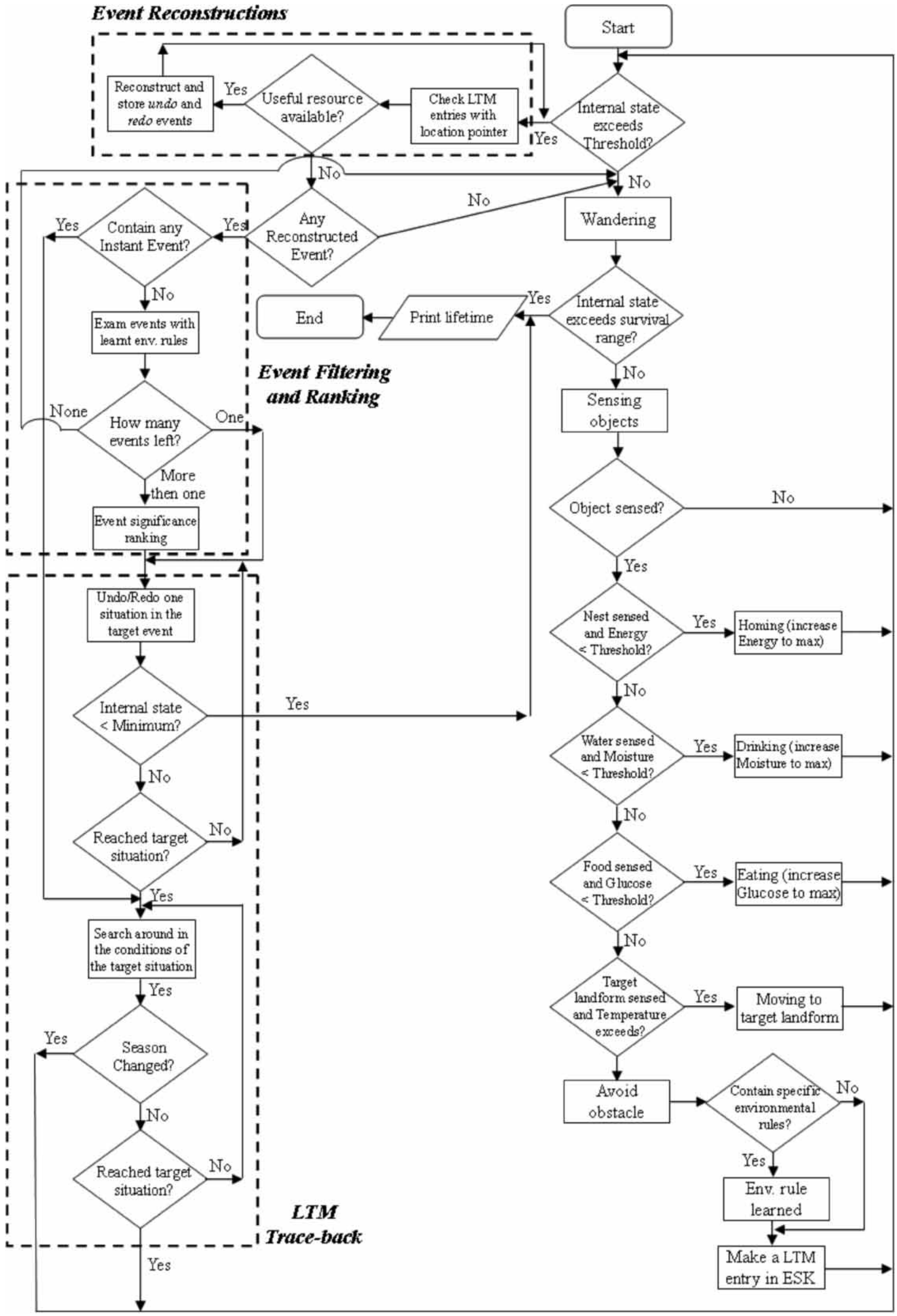

Figure B6. Data flow diagram of the Long-term Autobiographic Memory architecture.

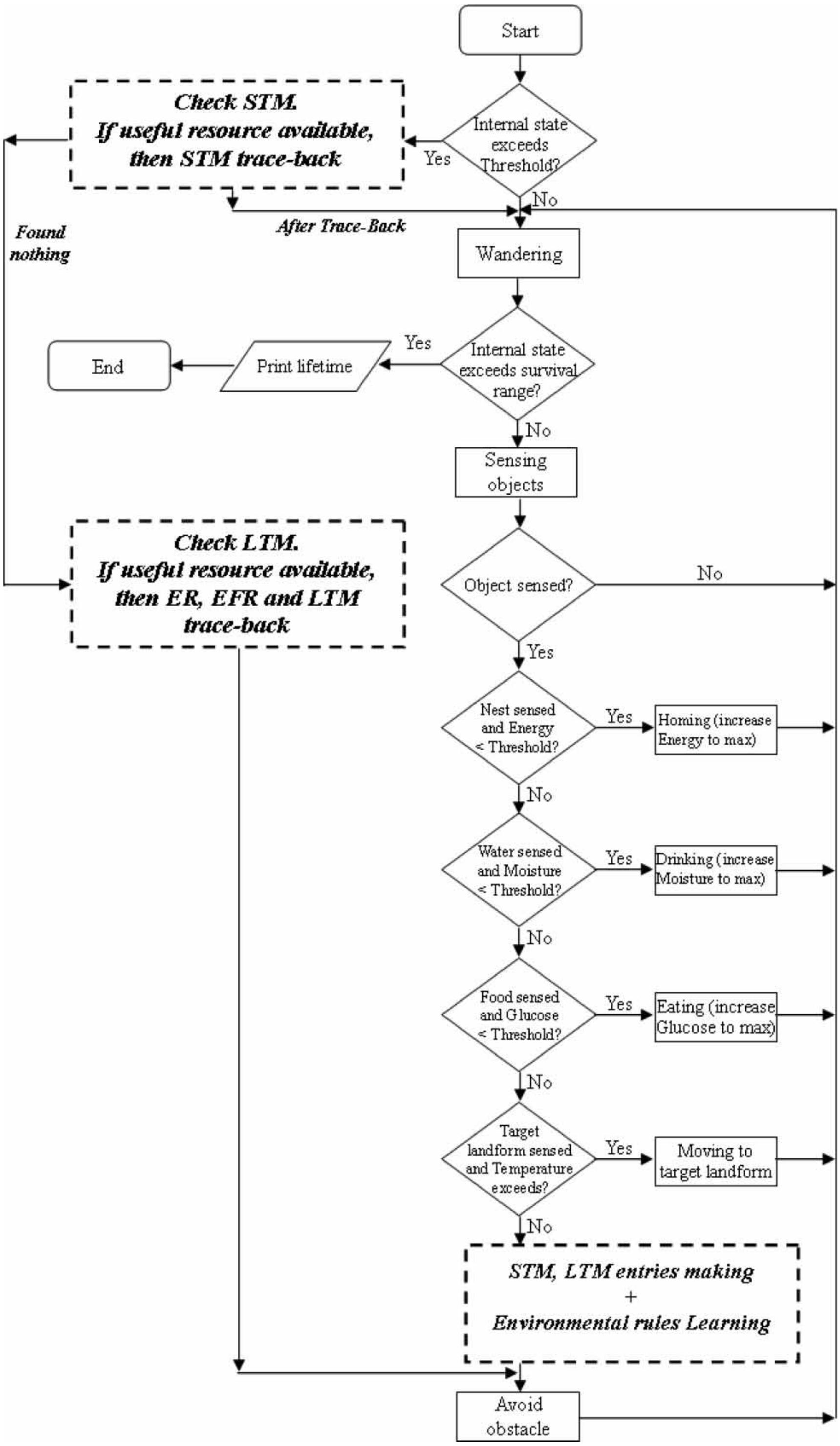

Figure B7. Data flow diagram of the Short-term and Long-term Autobiographic Memory architecture.

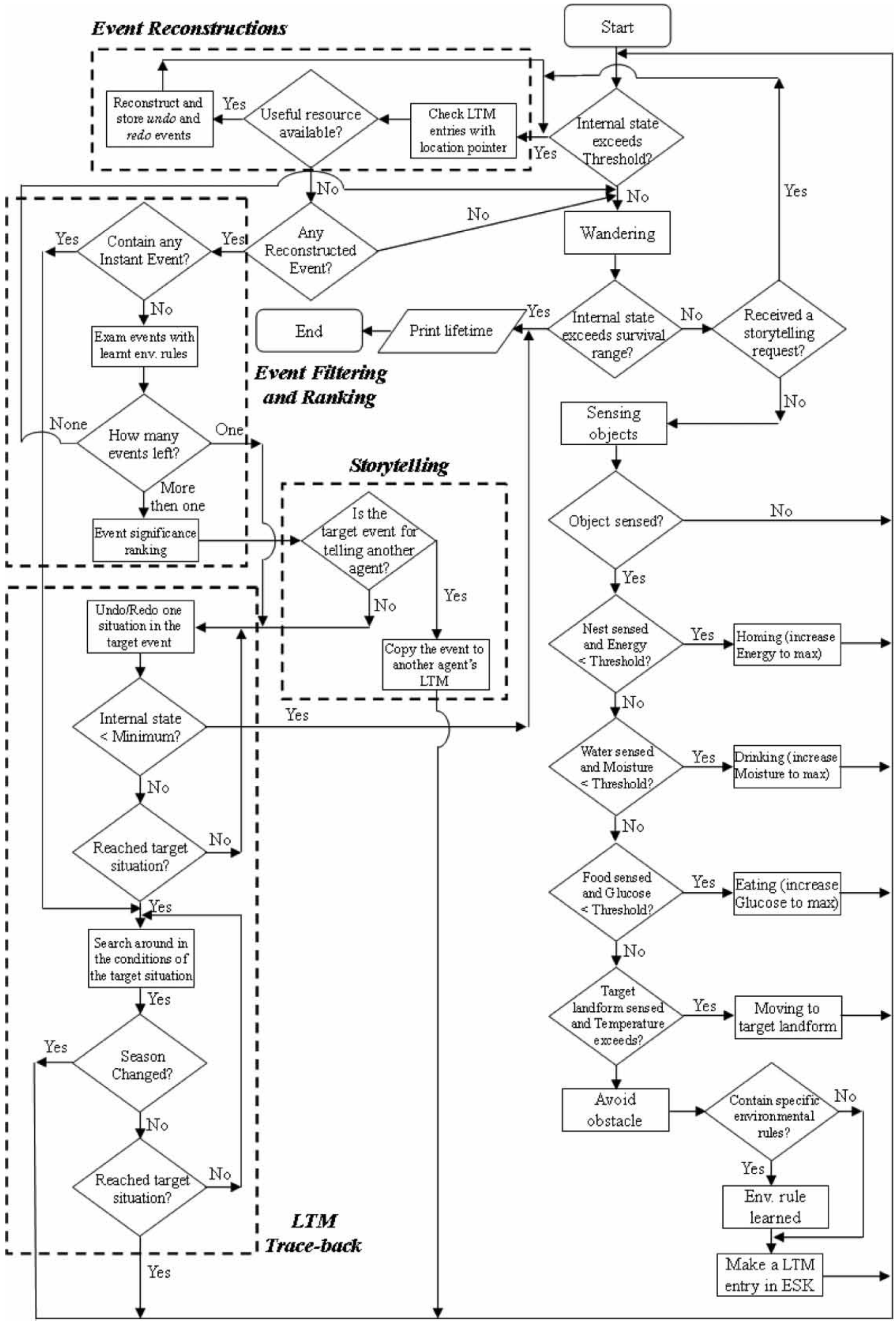

Figure B8. Data flow diagram of the Long-term Communicative Autobiographic Memory architecture.

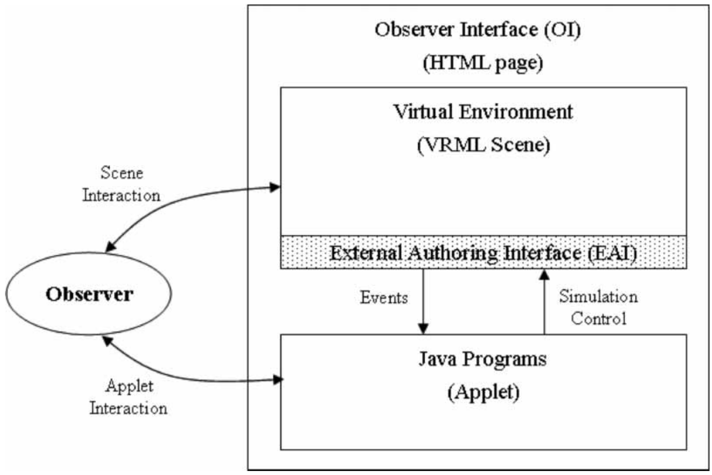

Figure B9. System diagram for the overall interactions between observer, virtual environment and Java Applet.

B.4. *Long-term autobiographic memory architecture*

Figure B6 illustrates the data flow diagram which represents the structured design of the Long-term Autobiographic Memory (LTM) architecture. Instead of displaying all memory entries in each time step, a LTM agent remembers new situations in ESK and only displays events reconstructed from ESK by using the Observer Interface when a Trace-back process is triggered. Environmental rules can be learnt if an LTM agent has experienced an irreversible event. These rules can help the agent to filter events violating any rule learnt. For the data structure of LTM in *Event Specific Knowledge* (ESK), see Figure 11 in Section 3.

B.5. *Short-term and LTM architecture*

Figure B7 illustrates the data flow diagram which represents the structured design of the Short-term and Long-term Autobiographic Memory (STM + LTM) architecture. STM + LTM architecture has both STM and LTM; therefore an agent can retrieve useful experience from both memories. The current setting is that STM has higher priority to be searched and reused if there is information regarding a useful resource. When the agent is not able to find anything useful in STM, LTM memory will be checked. Due to the space constraints in the diagram, details of STM and LTM are left out from the diagram.

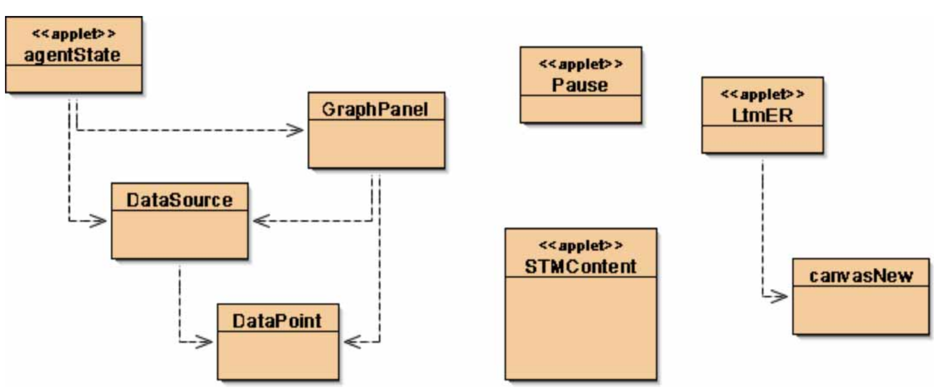

Figure B10. Java class diagram for the Observer Interface (OI).

B.6. *Long-term communicative memory architecture*

Figure B8 illustrates the data flow diagram which represents the structured design of the Long-term Communicative Autobiographic Memory architecture. This architecture is based on the LTM architecture and with the extra process to pass the event created from an agent's own LTM to the receiving agent.

B.7. *Observer interface*

Figure B9 shows the system diagram for the overall interactions between observer, virtual environment implemented by VRML scene and Java programs displaying agents' status and memory contents as well as providing the simulation control. Since VRML is an object description language for creating three-dimensional objects and scenes, it has limited functions and sensors for user interaction. To achieve displaying concise memory contents by using icons and agents' internal variables in a line chart which is continuously updated in each time step, at the same time providing simple control for the observer to pause the simulation in order to carry out detailed investigations in a particular moment, the External Authoring Interface (EAI) has been used to bridge the communications between the VRML scene and Java programs.

In each time step, the Java programs can receive events from the VRML scene through EAI, such as values of agents' current internal states, lifespan and various types of memory contents. Then each Java program class will display these events through different Applets in the Observer Interface (OI) on a HTML page. Figure B10 shows the abstract class diagram with relationships between Java classes. All classes can be divided into four groups:

- *agentState*, *GraphPanel*, *DataSource* and *DataPoint* classes show the agents' current status which includes lifespan and internal variables.
- *Pause* class pauses the simulation and displays the current season of the environment.
- *STMContent* class shows agents' STM contents through icons.
- *LtmER* and *canvasNew* classes illustrate the results of Long-term Autobiographic Memory ER process – all possible reconstructed events to be chosen to re-execute.