Episodic Memory for Human-like Agents and Human-like Agents for Episodic Memory

Cyril Brom

Department of Software and Computer Science Education
Charles University in Prague
Malostranské nám. 25, Prague, 118 00, Czech Republic
brom@ksvi.mff.cuni.cz

Jiří Lukavský

Institute of Psychology
Academy of Sciences of the Czech Republic
Politických vězňů 7, Prague, 110 00, Czech Republic
lukavsky@praha.psu.cas.cz

Abstract

Episodic memory has been approached from many levels of analysis and many of its facets have been modeled computationally. Recently, several models of episodic memory have emerged in the domain of intelligent virtual agents (IVAs). Compared to neuro-/psychological models, their plausibility is limited. On the other hand, they can store representations of large environments and other complex memories over long time intervals. This paper presents one such model and discusses the possibility of using IVAs as a test-bed to investigate neuro-/psychological models. The conclusion is that IVAs and their virtual environments can constitute an ecologically plausible framework allowing for study and integration of the neuro-/psychological models.

Introduction

Episodic memory is a multifaceted phenomenon; there are as many computational models as there are facets. Each discipline tends to only focus on a narrow range of aspects, adopting different terminology and different abstractions. They acknowledge the existence of memory phenomena out of the main scope of their models, but they do not address how their models could explain them. Can this state of affairs be improved?

The objective of this paper is to point out an emerging technology that may help with attempts to unify the presently fragmented computational research on episodic memory. This technology is virtual environments inhabited by *intelligent virtual agents* (IVAs), that is, agents imitating the behavior of a human or an animal, embodied in a 2D or 3D virtual world. In a nutshell, the suggestion is that this technology can serve as a test-bed for developing, investigating, and, importantly, integrating computational models of episodic memory.

The paper will start with a brief summary of computational models of episodic memory that have been developed and studied in cognitive psychology and cognitive neurobiology. Next, the paper will introduce the concept of IVAs and episodic memory models stemming from this field. These models depart from the models studied in cognitive neuro-/psychology (and also robotics) in an important way: they are aimed at modeling complex, rich, human-like episodic memories, which occur over long time intervals, e.g. hours, days, or even years; or representations of large environments full of land-marks and/or objects such as a city. This complexity is due to the relative simplicity of development of virtual environments, sufficiently abstract representations of these environments, and a near absence of noise from the agent's sensors. The cost is that plausibility of these models is disputable. Nevertheless, they are not typically intended to be plausible.

The main part of the paper will argue that this difference actually makes IVAs a suitable platform for investigating more plausible models computationally. For example, the last part of the paper will give an overview of our generic model, an IVA with a (non-psychologically plausible) episodic memory. The memory integrates following parts: visual short term memory, short term egocentric spatial memory, life-long allocentric "what-where" spatial memory, life-long autobiographic memory, and prospective memory (i.e. the agent's current and future plans). Presently the agent is partly implemented, both in a 2D virtual world and in a rich 3D world. The 3D implementation features useful developmental tools, tools for analyzing data (Kadlec et al. 2007), and is freely available to download.

The extended version of this paper provides more information on our model and describes related work (Brom, Korenko, and Lukavský 2008).

Episodic memories in neuro-/psychology

There are many models of episodic memory. They predominantly stem from cognitive psychology and neuroscience. While the psychological models tend to be more abstract and symbolic trying to describe mental algorithms, the neurobiological ones address how neural structures contribute to memory processes (Norman et al. 2008). The former predominantly aim at descriptive modeling of phenomena revealed in laboratory experiments like word list memorization or arithmetical calculation and produce models of verbal working memory or short term declarative memory (e.g. Miyake and Shah 1999). The latter are models of the neural substrate of the spatial memory – place cells, head-direction cells, and grid cells – or abstract connectionist models of formations of simple episodes (see Burgess 2007; McNaughton et al. 2006 for a review; see also Rolls et al. 2002; Samsonovich and Ascoli 2005).

It has been argued that psychological models do not support the representation of complex real-world episodes (e.g. Kokinov et al. 2007) but neither do neurobiological models. Both kinds of models are oriented on short-term intervals, e.g. seconds or minutes. Generally, the neurobiological area of work is fragmented, but interested in integrating models of various individual phenomena (e.g. Samsonovich and Ascoli 2005; Eichenbaum 2004). This fragmentation is apparent in the psychological domain as well. It is probably no accident that several cognitive architectures have been recently extended by complex episodic memory models; namely Soar (Nuxoll 2007), ACT-R (Schultheis, Lile, and Barkowsky 2007), and LIDA (overviewed in Franklin et al. 2005), providing architectural frameworks for implementation of agents with both high-level cognitive and episodic memory abilities. However, only few agents have been really implemented within these frameworks to date. The important questions now are whether IVAs can make the neuro-/psychological models better, and how will they do so?

Episodic memories in IVAs

The notion of an *intelligent virtual agent*, basically a piece of software that can be considered as *autonomous* in some manner and at the same time *graphically embodied* in a 2D or 3D virtual environment, began to emerge about a decade ago, capitalizing on the general agent metaphor (Wooldridge 2002). Various kinds of applications feature IVAs, including computer games, cultural heritage, cognitive science research, and computational ethology.

Building IVAs, like agents in general, is hard. Besides graphical issues, which can be a major task by themselves, there is the behavioral side of the problem. Firstly, IVAs act in dynamic, unpredictable, interactive worlds that typically run in real-time. Secondly, the simulation of IVA behavior entails many multifaceted objectives. These range from navigation and movement through accomplishing complex cognitive tasks, to social interaction, communication and emotional responsiveness. Large scale projects, e.g. computer games, feature scenarios with tens of IVAs and moving objects, such as cars.

The important concept behind IVAs is *believability*, which, basically, is the *imitation* of human or animal-like behavior to make IVAs life-like. The believability does not equal *plausibility* in the sense of building a computational model to verify/falsify a theory/model. Whether an IVA will tend to be believable or plausible depends on its authors' objectives. For computational ethology, the plausibility is most important, but the graphical representation is not. In entertainment applications, the believability counts. Here, it is important that it is *possible* in principle to make IVAs neuro-/psychologically plausible.

Several IVAs with relatively complex episodic memory models have been developed recently. Some IVAs have been developed with spatial memory to increase believability of navigation and/or "what-where" judgments (Thomas and Donikian 2006; Strassner and Langer 2005; Peters 2006; Isla and Blumberg 2002; Noser et al. 1995). Other IVAs have been equipped with autobiographic memory for the purposes of explaining themselves after they teach a lesson (Rickel and Johnson 1999; Dias et al. 2007). Also there has been work at the intersection of the IVAs field and artificial life, which investigates how different types of autobiographic memories can improve an agent's chances of survival (Ho, Dautenhahn, and Nehaniv 2008).

Most of these models are symbolic and, typically, are loosely inspired by psychological data. For example, they tend to reflect the classical short-term/long-term memory distinction. The way that these models depart most from the neuro-/psychological models is that they are aimed at representing complex, rich, human-like episodes, or large spaces such as a city with many landmarks and objects, as opposed to a list of verbs or a topology of a single location. If a forgetting mechanism is implemented, the models can be used in scenarios lasting long time intervals, e.g. days.

IVAs as a cognitive science research platform

This section will argue that 1) IVAs are in an excellent position to constitute a platform for testing and integrating neuro-/psychological memory models; and that 2) with their help a new set of phenomena concerning representing complex episodes, complex environments and life-long memory can be investigated computationally.

1) The virtual worlds *plus* IVAs constitute the platform. The main proposal is that one can integrate his or her model, tailored to a restricted set of phenomena, e.g. localization, with a more abstract, but relatively general computational model, that is, into an episodic memory model of an IVA, which is itself only a part of a larger model, that is, the IVA's "mind". The implanted model will then become a part of the IVA's perception–action process, which itself is "embodied" in a virtual world. This is a relatively ecologically plausible model of the real world, it provides a semi-continuous stream of rich sensory data (e.g. at 15 Hz) as well as a complex environment for acting.

2) Virtual worlds change one's thinking. This process of implantation forces one to think about new kind of issues. Metaphorically, when creating a virtual hippocampus for an IVA, one *must* connect the hippocampus to the whole virtual brain, i.e. to create interfaces; otherwise, the IVA will not act (but note that the "whole brain" can be quite abstract from the point of view of the hippocampal model). This requires the developer, at least to some extent, to explicitly consider issues lying *out* of the scope of his or her model. The input data becomes more rich compared to a simple “laboratory environment” created in Matlab. The output data has to meaningfully contribute in generating complex human-/animal-like behavior. For the similar reasons, many researchers implement their models on robots (e.g. Krichmar et al. 2005).

3) What is so special about virtual worlds in comparison to environments of robots? In virtual worlds, the walls, objects, and their positions (including IVAs) are typically represented explicitly, hence their extraction for the purpose of an IVA is much simpler that in robotics. Virtual worlds are “more abstract” than the reality, which allows one to abstract from many details and concentrate on high-level issues (but to also consider the broader context at this higher level of analysis at the same time – see §2). Consequently, worlds of IVAs are much larger and more complicated than environments of robots. These features can facilitate a) the investigation of present-day models in richer contexts, b) focusing on new issues, e.g. the representation of complex spaces and episodes.

Virtual reality is quite flexible in levels of modeling, an important advantage. On one hand, semantic knowledge can be represented within a virtual environment in a highly abstract way, e.g. “this is a place from which I can shoot”, or “this is an object I can use for accomplishing a goal of watering a garden”, a reminiscence of the notion of affordance (Gibson, 1979; see also Brom et al. 2006). This “semantic perception” is largely unavailable to robotic artifacts (for a robot with a simple episodic memory see Dodd 2005). On the other hand, low-level perception processes can be imitated via ray-casting, a mechanism through which an IVA can see the underlying geometry of the virtual world similarly to how robots use their sensors. Both approaches can be combined.

4) Is the level of abstraction appropriate? Summarizing the argument so far, virtual reality allows one to avoid many low-level issues that need to be addressed in robotics, and, at the same time, *forces* one to consider new issues stemming from the richer environmental context of a virtual world. Going from the robotic world to the virtual one brings one closer to reality in one sense at the cost of losing some detail in another – this is a trade-off. We argue that for the episodic/spatial memory modeling, the time has come to follow this path towards the more abstract but complex waters because the neural correlates of the declarative memory processes seem to be situated rather at higher cortical areas than primary sensory cortices, which means that the modeler has to consider inputs which are already pre-processed, and thus abstract, in some way. Had one modeled the retina or motion generation, robots or a “Matlab environment” may have been better choices.

5) A novel research paradigm. When having a model implemented in a virtual world (using an IVA), one can collect the data and compare them with data generated by real humans acting in the same setting. This setting can be more complex than settings of present-days neuropsychological experiments using virtual reality, e.g. one can investigate episodic memory of human and artificial players of a multi-player online role-playing game over weeks.

An agent with episodic memory

We have been developing an IVA with episodic memory (Brom, Pešková, and Lukavský 2007; Brom, Korenko, and Lukavský 2008). The motivation is to create a generic and believable agent with episodic memory, which can be used in videogames featuring a large world evolving over long time. Such a generic agent has not been developed yet, though several special-purpose models are already available (see above). This section illustrates the architecture of our IVA and the memory module.

Generally, the model stores information in an abstract way and also uses abstract input information. It is an ongoing project and presently we have three independent implementations of various parts of the model, two of them employing a 2D grid world, the last one using a 3D world of the action game Unreal Tournament (Epic 2004). All of these simulations employ discrete time, one time step in the game equates to a couple of seconds. Conceptually, the model integrates following parts: a visual short term memory (visual STM), a short term egocentric spatial memory (work-in-progress), a life-long allocentric spatial memory for “what-where” information (LTSM), a life-long autobiographic memory (LTEM), and a simple prospective memory. The most developed part to date is the LTEM.

Reasoning mechanism. The agent’s overall architecture is depicted in Fig. 1. It is a reminiscence of a classical cognitive AI architecture, from which many IVAs have been inspired. The IVA is driven by hierarchical reactive planning with behavior represented by *AND-OR trees*. The AND-OR tree metaphor works with abstract *goals* representing what shall be achieved, and *tasks* representing how to achieve the goals. Typically, every goal can be accomplished by several tasks, while every task can be achieved by adopting some sub-goals. The agent needs to perform only one task to achieve a goal, provided there is no failure (hence, OR nodes); but to fulfill all sub-goals to solve a task (hence, AND nodes). The tasks that cannot be further decomposed are *atomic actions*, i.e. action primitives. Every task may need several resources to be performed, i.e. *objects*. Every top-level goal has its *activity level* based on drives, external events, and a schedule. The competition among the goals based on this level takes place within the *goal structure*, which also stores the AND-OR trees. The winning goal chooses the most appropriate task (e.g. “to eat” goal can chose “take something from the fridge”) and passes its template to the *task field* of the short-term memory. One goal can interrupt another, in which case the tasks of the interrupted top-level goal are remembered and can be resumed after the more important goal is achieved.

From an AI standpoint, this mechanism capitalizes on the BDI framework (Bratman 1987; Wooldridge 2002), which is employed in many IVAs. Our agent is reactive, meaning it considers its actual state and new percepts in every time step, but does not create plans for the future. Many IVAs work in this way; even though the BDI allows for creating future-oriented plans as well. The task field is a basic form of *prospective memory* (and perhaps working memory in a broader sense). In our model, this component stores the top-level task the IVA is working on to accomplish a top-level goal, its subtasks, and possibly other tasks that have been interrupted and are to be resumed. Had we employed the future-oriented planning, the memory would have also stored the future-oriented tasks.

Visual short term memory. The visual STM holds templates of objects seen that passed through a simple *attentional filter*. Visual STMs and attentional filters are common in current IVAs, for both engineering and believability purposes. The object templates are called *phantoms* in our model. Every object is regarded as a tool for action, i.e. it *is* a set of "affordances" (Gibson 1979), meaning it possesses pointers to the tasks it can be used as a resource for. These pointers are actually perceived directly by the agent when observing its environment, a demonstration of a high-level representation of input information. Objects in our experiments are state-less for the sake of simplification, though our simulations allow the objects to have states as well. Positions are represented in the 2D Cartesian frame of reference. Presently, there is no additional information stored in this memory. Due to a *decay mechanism*, there can be about 8-10 phantoms in the STM. The memory can also temporarily hold information about an object recalled from the LTEM (MF at Fig. 1).

LTEM. The LTEM represents what happened to the agent in the past. From the point of view of the IVAs field, this particular mechanism presents a novel contribution. The memory is a tree-like structure comprising all the possible tasks the agent can perform (Fig. 2). During recall, two types of entities are added into this structure: phantoms, and so-called *time pointers*. Each phantom in the LTEM represents an object used as a resource in a task in a particular moment, or an object that was not used but attracted the agent's attention. The time pointers represent the course of events. The remembering happens continuously; phantoms are copied from the visual STM and time pointers are created based on the content of the task field. It is quite straightforward to extend this mechanism by storing other information, e.g. the internal state of the IVA.

The important feature of the LTEM is *forgetting*: unimportant episodes (i.e. their time pointers and phantoms) are being "eaten away" from the bottom of the tree-like structure (Fig. 3), typically during the night during "consolidation". The episode's importance is determined by its age and emotional salience. This mechanism allows the IVA to forget details of an episode but still remember its "gist"; note, however, that it is still "binary" in some sense: a particular record either present, or not. Episodes can not be blended – presently this is the greatest challenge we face.

The tree-like structure mirrors the AND-OR trees stored within the goal structure, hence it is determined in advance by the designer of the system. Consequently, the IVA is not able to store what *other agents* are doing. To do so would require a mechanism that would allow the IVA to directly perceive symbols denoting actions of the other agents, along with templates of these actions preprogrammed into the IVA's tree-like structure.

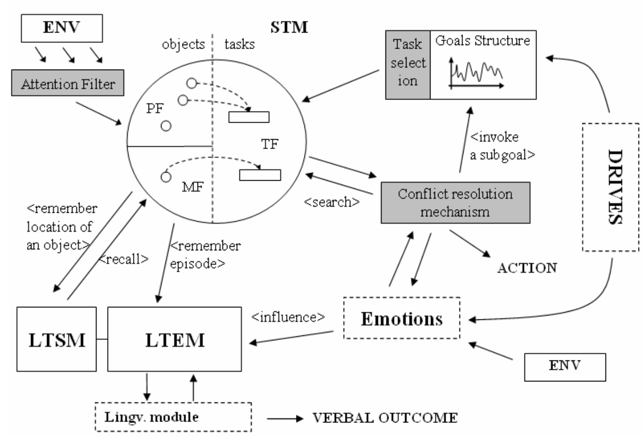

Fig. 1. The overall architecture of our agent. Note the perception—action cycle. ENV – the environment. PF – phantoms of the visual STM. MF – phantoms retrieved from the spatial long-term memory. TF – the task field. LTEM – the autobiographic memory. LTSM – the long-term spatial memory.

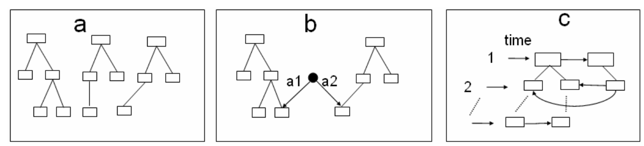

Fig. 2a. The tree-like structure of the LTEM, each box represents a task. 2b. Storage of a phantom of an object. The object can be used as a resource for two tasks (pointers *a1*, *a2*). 2c. The tasks are sorted by time pointers during storing automatically.

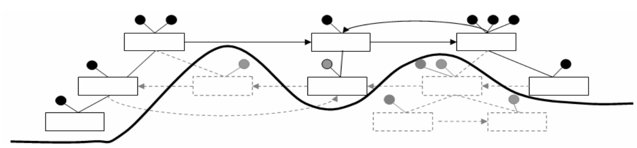

Fig. 3. The LTEM forgetting schematically depicted.

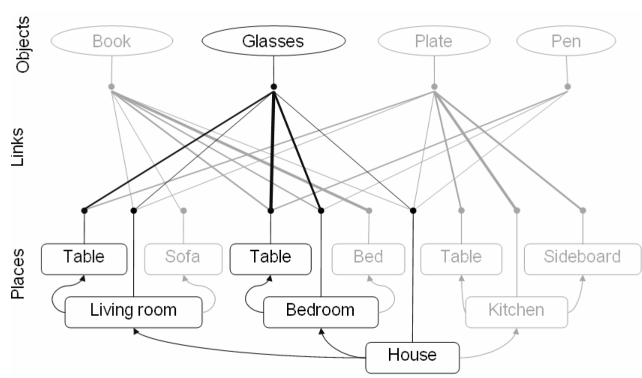

Fig. 4. Spatial memory. The glasses links are highlighted.

LTSM. Our IVA "reads" the structure of the environment directly from the map of the world, which corresponds to a perfect knowledge of the topology. This is implausible and it may result in unbelievable behavior. However, topological memory is beyond the scope of our present work (Thomas and Donikian 2006 address this issue). We focused on "what-where" memory, i.e. memory for positions of objects that are passive but whose locations can be changed by external forces. This is an issue which has yet to be addressed appropriately by the IVAs community (for a memory of actively moving objects see Isla and Blumberg 2002). If a task requires an object that is not seen by the agent, i.e. there is no relevant phantom in the visual STM, the IVA should query its LTM and initiate the environmental search. However, as the virtual world is dynamic, positions of objects can change beyond the agent's capabilities. Therefore, if the IVA queries the LTEM, more phantoms concerning one object can be found ("where are the glasses: at the bedside table, or at the working table?"). Using the simple heuristic "pick the most recent phantom" often led the agent to search in the wrong places.

How can we improve the performance? Consider the objects that humans use. Humans have some organization of the placement of their belongings. Things are not placed randomly within our surroundings. They are clustered purposefully according to our needs and cultural norms. Some objects appear regularly at some places (newspapers inside a mailbox). Other objects are almost never being relocated (a van Gogh's painting). Yet others are being relocated so often that it is not practical to remember their exact position. Consequently, when a human searches for an object, often, a sort of stimulus-response mechanism is employed. For a different object, several places are inspected in a specific order; sometimes, the whole house is scrutinized but starting at a specific place. This brings us to the notion of *searching rules*, which are basically a sequence of places that should be inspected when searching for an object of a particular kind. By place we mean any logically coherent space abstraction independently of its size, capitalizing on hierarchical nature of how humans cluster space; e.g. a bedside table, a place between this table and the bed, a corner of the living room, a living room, a flat, etc.

We have developed a mechanism that estimates the likelihood of finding an object at various places. This is the long-term spatial memory for "what-where" information (the LTSM). We hypothesize that *if we apply this mechanism in an IVA living in a human-like environment, believable searching rules will emerge.* (We mean the believability in an intuitive manner for we had and have no data to compare the model with). The LTSM is composed of two kinds of nodes: objects and places. Object nodes have weighted links with place nodes; these stand for "what-where" information: a possible occurrence of a particular object at a particular place. Now, if an object is found by the agent, or comes to the agent's attention, the links to *all* the locations where it has been found are strengthened (e.g. the links from the pen to a) the bedside table, b) to the bedroom, and c) to the whole flat – Fig. 4). Essentially, the searching rules emerge from this hierarchical aspect of the representation. How is this possible? First, links to nodes representing places at a similar level of complexity approximates the probability distribution of finding the object at given places. Secondly, links to nodes representing more abstract places are strengthened more often than links to nodes of concrete places. Now, if the LTSM is queried for an object position, we can sort the place nodes that the object node share an edge with according to the strengths of the links scaled by the inverse function of the size of the places the place nodes are referring to. The object will be looked for according to the ordering that is produced. Concrete places are searched directly (e.g. the bedside table) while abstract places are to be inspected (e.g. scrutinize the kitchen). This leads to a searching process that prefers concrete places to abstract ones, provided that there are only a few concrete places where the object can be found. Otherwise, the agent prefers to inspect abstract places.

Summary of results. The model has been tested in scenarios lasting a couple of days, in which the IVA acted in an environment the size of a house. Presently, we are working on an environment the size of a city. The information in the LTEM is used to construct "personal stories" of the agent. Regarding the LTEM, we measured how the memory grew over time. The amount of stored data was acceptable when forgetting was switched on. Regarding the LTSM, we mainly looked for the emergence of searching rules. It turned out that they really emerged. In sum, both the LTEM and the LTSM, the most important and most developed parts of the model, behaved well, although several limitations were revealed. More details can be found in (Brom, Korenko, and Lukavský 2008).

Conclusion and Future Work

This paper has considered the possibility of using IVAs to aid in the computational modeling of episodic memory. The main argument was that virtual environments, such as the environments of the action game Unreal Tournament (Epic 2004), are somewhat ecologically plausible models of real worlds, while IVAs present vehicles for testing the episodic memory models. They generate input data for these models and allow output data to be meaningfully manifested. IVAs have quite elaborate architectures, which are not monolithic but modular. This allows for the replacement of one module with another and allows new mechanisms to be added easily to the existing system. Compared to a robotic platform, virtual reality is more technically accessible and allows for investigation of higher-level phenomena, such as complex episodes or evolution of representations of large environments over long periods – aspects of episodic memory that have not been much studied computationally yet. The drawback of this is a loss of detail. This paper has also suggested that it is in principle possible to conduct longitudinal studies in virtual reality settings with human subjects and compare the data gained with data produced by the models embodied in the same virtual setting. Our main work in progress includes:

- Two mechanisms that extend the autobiographic memory. The first operates by a kind of activation-spreading network similar to the one used in ACT-R and LIDA, connecting phantoms of objects that has some semantic relations. The second is a neural network that mimics biological clocks, which will replace time-pointers. These two mechanisms should help the modeling the blending of similar episodes and more believable cueing on time.

- A mechanism that will learn space representations. Currently the LTSM uses hard-wired representations.
- A short-term egocentric spatial module which takes into account some psychological data.
- Researching the possibility of underpinning the autobiographic memory by a connectionist architecture. One possibility being considered is the Kanerva's space distributed memory (Kanerva 1988), an inspiration coming from the LIDA architecture.

Acknowledgement

Several students contributed during development of the model: K. Pešková, T. Korenko, O. Burkert, T. Soukup, and J. Kotrla. The authors also thank to following researchers for their helpful comments: R. Šikl, K. Vlček, U. Ramamurthy, and R. J. McCall. This work was partially supported by the Program "Information Society" 1ET100300517, and by the Ministry of Education of the Czech Republic (Res. Project MSM0021620838).

References

Bratman M. E. 1987. *Intention, plans, and practical reason.* Cambridge, Mass: Harvard University Press.

Brom C., Lukavský J., Šerý O., Poch T., Šafrata P. 2006. Affordances and level-of-detail AI for virtual humans. In *Proc. of Game Set and Match 2*. 73-82.

Brom, C., Pešková, K., Lukavský, J. 2007. What does your actor remember. Towards characters with a full episodic memory. In *Proc of 4th ICVS*, LNCS 4871. 89-101. Berlin, Springer-Verlag.

Brom, C., Korenko, T., Lukavský, J. 2008. How Place and Objects Combine? Long-term Spatial Memory Enhanced by Objects for Human-like Agents, Tech. Rep 05/2008, Dept. Software and Comp. Science Education. Charles University in Prauge.

Burgess, N. 2007. Computational models of the spatial and mnemonic function of the hippocampus. In *The Hippocampus Book*, 715-750. Oxford University Press.

Dodd, W. 2005. The design of procedural, semantic, and episodic memory systems for a cognitive robot. Master thesis. Vanderbilt University, Nashville, Tennessee.

Eichenbaum, H. 2004. Hippocampus: Cognitive Processes and Neural Representations that Underlie Declarative Memory. *Neuron* 44: 109-120.

Epic Epic Games: UnrealTournament 2004. http://www.unrealtournament.com [15. 6. 2008]

Franklin, S., Baars, B.J., Ramamurthy, U., Ventura, M. 2005. The role of consciousness in memory. *Brains, mind, media* 1: 1-38.

Gibson, J. J. 1979. *The Ecological Approach to Visual Perception*. Boston: Houghton Muffin.

Ho, W., Dautenhahn, K., Nehaniv, C. 2008. Computational Memory Architectures for Autobiographic Agents Interacting in a Complex Virtual Environment. *Connection Science*. In press.

Isla, D., Blumberg, B. 2002. Object Persistence for Synthetic Creatures. In *Proc. AAMAS'02*, 1356-1363.

Kadlec, R., Gemrot, J., Burkert, O., Bída, M., Havlíček, Brom, C., 2007. POGAMUT 2 - A platform for fast development of virtual agents' behaviour. In *Proc. of CGAMES 07*. 49–53.

Kanerva, P. 1988. Sparse Distributed Memory, The MIT Press.

Kokinov, B., Petkov, G., Petrova, N. 2007. Context-Sensitivity of Human Memory: Episode Connectivity and its Influence on Memory Reconstruction. In *Modeling and Using Context*, LNCS 4635. 317-329. Berlin, Springer-Verlag.

Krichmar, J. L., Seth, A. K., Douglas, A., N., Fleischer, J. G., Edelman, G. M. 2005. Spatial Navigation and Causal Analysis in a Brain-Based Device Modelling Cortical-Hippocampal Interactions. *Neuroinformatics* 3(3): 197-221

McNaughton et al. 2006. Path integration and the neural basis of the 'cognitive map'. *Nature Reviews Neuroscience* 7: 663-678.

Miyake, A., Shah, P. eds. 1999. *Models of Working Memory: Mechanisms of Active Maintenance and Executive Control*. Cambridge University Press.

Morris, R. 2007. Theories of hippocampal function. In *The hippocampus Book*, 581-694. Oxford University Press.

Noser, H., Renault, O., Thalmann, D., Magnenat-Thalmann, N. 1995. Navigation for Digital Actors based on Synthetic Vision, Memory and Learning. *Computer and Graphics*, 19(1): 7-19.

Norman, K. A., Detre, G. J., Polyn, S. M. 2008. Computational models of episodic memory. In *The Cambridge Handbook of Computational Cognitive Modeling*. In press.

Nuxoll, A. 2007. Enhancing Intelligent Agents with Episodic Memory. Ph.D. diss. The University of Michigan.

Peters, C. 2006. Designing Synthetic Memory Systems for Supporting Autonomous Embodied Agent Behaviour. In *Proc. RO-MAN06*. 14-19.

Rickel, J., Johnson, W. L. 1999. Animated Agents for Procedural Training in Virtual Reality: Perception, Cognition, and Motor Control. *App. Artificial Intelligence* 13(4-5): 343-382.

Samsonovich, A., Ascoli, G.A. 2005. A simple neural network model of the hippocampus suggesting its pathfinding role in episodic memory retrieval. *Learning & Memory* 12: 193-208

Schultheis, H., Lile, S., Barkowsky, T. 2007. Extending ACT-R's Memory Capabilities. In *Proc. of EuroCogSci'07*, 758–763.

Strassner, J., Langer, M. 2005. Virtual humans with personalized perception and dynamic levels of knowledge. *Comp. Anim. Virtual Worlds* 16: 331-342.

Thomas, R., Donikian, S. 2006. A spatial cognitive map and a human-like memory model dedicated to pedestrian navigation in virtual urban environments. In *Proc. Spatial Cognition V*, LNCS 4387. 421-436. Berlin, Springer-Verlag.

Wooldridge, M. 2002. *An Introduction to MultiAgent Systems.* John Wiley & Sons.