The Web as an Autobiographical Agent

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Abstract. The reward-based autobiographical memory approach has been applied to the Web search agent. The approach is based on the analogy between the Web and the environmental exploration by a robot and has branched off from a currently developed method for autonomous agent learning of novel environments and consolidating the learned information for efficient further use. The paper describes a model of an agent with "autobiographical memories", inspired by studies on neurobiology of human memory, the experiments of search path categorisation by the model and its application to Web agent design.

1 Introduction

Autonomous agents have traditionally been built on the grounds of detailed models, focused tasks, or common-sense heuristics, i.e. the top-down approach. Autonomous agents approach is common in Web modelling, soft computing and intelligent robotics among other application fields [1]. In this paper we make a parallel between a robotic and a Web autonomous agent. Intelligent robotics agents have to fulfil various tasks independently and to decide when and what kind of initiative to undertake. Web agents are similar to robots in that they have sensory-perceptual/logical input, the goal to achieve, and they perform within the limits of the implemented algorithms. Recent research, however, has shown that it is technically justified to build intelligent robots on the grounds of neurobiology [2], [3]. It turns out that the neurologically plausible autonomous robots/agents achieve higher behavioural flexibility and goal attainment and are superior to the ones that count on complex, but exact computational heuristics [4], [5], [6]. A higher level of "intelligence" is demonstrated when the robot can efficiently make use of the previously encountered events [6], [7]. This involves not just memory in the

C. Bussler and D. Fensel (Eds.): AIMSA 2004, LNAI 3192, pp. 510–519, 2004.

computational sense, i.e. memory as a stack or storage, but human-like memory, that accounts for concept change, source monitoring, novelty/familiarity detection and goal reformulation [8]. In this paper we hypothesise, that if a Web agent incorporates autobiographical knowledge in terms of "human-like memories" sense, it will be able to interact with the user in a more meaningful way.

Traditionally, cognitive science has produced general models of human cognition, learning and behaviour that, however, lack the diversity of individual user daily experience. The semantics of the interaction of the user with the Web has to be able to convey not just facts, statements, definitions, i.e. the so-called "cold" knowledge, but also "hot" opinions, reviews, intentions, and nuances in user communication within the Web [9]. Moreover, this has to account for user previous Web experience. In trying to build these micro-components of an intelligent Web agent we have turned to cognitive science looking for insights or "smart heuristics" to make them both simple and efficient and perhaps brain-like in their "attitude" to the user [10]. What we have found is abundance of approaches that need to be investigated further. We feel that the Web provides the perfect medium to understand those micro-aspects of cognition and to build Web agents, which are small in size and very adapted, placed on a single server and accessible from any place in the world.

The paper addresses three interrelated research issues we are currently pursuing. The first one is a model of a robot based on episodic/autobiographical memories, inspired by studies on neurobiology of human memory. The second is the interpretation of the autobiographical robot as an intelligent agent similar to Web agents, and the third is an example of a "short-term memory-like" Web agent with its attractive interface features and difficulties in "understanding" the user. We feel the issue of building autonomous/autobiographical agents to account for user experience with the Web is essential to the process of building the new Semantic Web.

2 Agents with and Without Human-Like Memory

At present, intelligent robots are able to perform tasks with different degree of autonomy. Experimental robotics has shown that autonomous systems can be built by simulating, for example, insect-like behaviours. We aim at higher level of intelligent behaviour, which has as a bottom line flexibility - to use its old experiences in novel situations. At present, even higher forms of intelligence, derived from imitation learning, is an object of robotics applications [2], [3], [4]. Since the actual processes underlying this type of behaviour are understood on a very coarse level only, it does not meet our present research objectives.

Computer science and robotics exploit the characteristics of the semantic memory - memory for facts. Actually, memory for events and their relatedness is the way higher organisms build their knowledge; moreover, episodic memory copes naturally with the sensory, perceptual and behavioural character of learning of an embodied agent. In our study novelty is considered a gating factor for forming episodic memories during learning and familiarity - a mechanism for inferential use of episodic memories while behaving in a novel Web environment. The so stated scope puts forward memory-based behaviour, which includes remembering of past events, familiarity detection involved in episodic memory formation and the respective more effective Web behaviour, corresponding to the interests/needs of the user. The basic difficulty, as we will show, is how to reasonably infer future user interests from browsing behaviour. The autobiographical approach is able to predict more consistent future requests than the "straightforward" one.

3 Hypothesis: Episodic and Autobiographical Memory Underlie Intelligent Action

There have been many speculations of what intelligence and intelligent behaviour is. Yet, an exact definition is not available. Instead of elaborating on the subject, we will define the range of intelligent behaviour that is plausible for our study. We aim at a level of intelligence that allows transfer of the previously acquired knowledge into a new task. Therefore, memory is the intrinsic requirement for our intelligent system.

Extensive research in neuroscience [11], [12], [13] has shown that there is a specific brain structure - the hippocampus - that encodes episodic memories (EM). The episodic memories lay the context of the studied task - sensually/perceptually/emotionally coloured, yet underlying the acquisition of new and restructuring old, declarative knowledge (knowledge for facts and events, not for learning skills). Its characteristic feature is the "when" question - the explicit reference to the exact moment when a given event took place, like learning new knowledge or meeting an old friend, for example. EM has got temporary structure in terms of one-to-several hours. Hence the main difference from the so-called autobiographical memory (AM) where the "when" aspect is often difficult to retrieve.

Fig. 1. Schematic representation of the interactions between HF and NAA, to support the EM-AM connection

Although AM in general consists of episodes and spans lifetime, the "when" notion is frequently lost and compensated with the "what" notion. And this constant re-categorisation and "renewal" of old memories relates and interrelates to the semantic memory acquisition process, generally taking place in the interaction between the hippocampal and the cortical processes/areas (Fig. 1). Web search has similarities with exploring a new environment and finding one's way in it, this way the environment is constructed of keywords and concepts as analogy to views and itineraries [14].

To connect Web modelling with the episodic memory paradigm and brain-like computing in general, the following hypothesis is made. Web search resembles the exploration and successful information finding processes, as experienced by a navigation activity. During the interaction of a user through a Web engine with the information on the net, the Web agent remembers the successful searches and the most satisfying findings of the user and serves as an optimisation tool for doing new search.

4 Autobiographical Web Agent Concept

The aim of the autobiographical Web agent is to learn the meaningful steps and directions by Web explorations and use them as an optimisation criterion by the next searches. In analogy with a robot exploration task, finding meaningful information is equivalent, for the particular user, to either (sub-) goal or landmark encounter. As an initial step, the encountered useful concepts (keywords) are clustered by an on-line clustering algorithm, in which the characteristic concepts are stored as representatives.

The clustering algorithm uses the following principle. Clusters that often come in a subsequent order get laterally connected, forming episodes. These connections get active by the arrangement of the search results. Let us assume that an episode is formed by three elements: sensing, perception, and evaluation. In formula (1) episode W is a triple,

$$w = (s, p, a)\,, \tag{1}$$

where s, p, a are the sensory, perceptual and evaluational component, respectively. An episode evolves over time under these three influences:

$$\frac{dW}{dt} = f(s + p + a)\,, \tag{2}$$

where f denotes functional dependence.

A search task consists of finding a discrete item of information. Such an item will be further referred to as an event. A Web search episode is a set of n discrete events occurring in temporal order e_t, ($t \in [1,\ldots,n]$), defined by a considerable difference in the event representations. $W = \{w_t\}$, $t \in [1,\ldots,n]$. A single event w_t is defined by the user input s, and p and a, that denote the feedback of the remembered searches (previous searches from the same user) and the evaluational influence. The sensory component s_t refers to the user's current choice and p_t and a_t components are based on previous experience. Here, s_t introduces the influence from the external user and constitutes of feed-forward connections; the perceptual component p_t represents the internal influences and is performed by lateral connections; the reward component a_t represents the influence of the previous actions as brought on the current event. The change from one to another event requires a change in at least one component that is bigger than an internal threshold, indicating the detection of a novel event.

The sensory as well as the reward (evaluational) signals are encoded in unique patterns of activity. These patterns are external-world related. The formation of the internal representations is conceptually motivated by the Piagetian self-supervised paradigm for learning target-oriented behaviour [15]. The essential feature for enabling brain maps to handle this rule is the capacity for topologic organisation, which allows an internal representation of the external space emerge in a coordinate-free way [16]. A good deal of work has been carried out on the ways in which simple, self-organising heuristics can produce such internal representations, from the early work of Kohonen [17] to the recently developed growing self-organising algorithms [18].

Instead of relying on artificial heuristics that perform topological organisation, we have chosen Hebbian learning for episodic encoding. The Hebbian rule most closely simulates the known brain computational mechanisms. The required self-organisation properties can be obtained by lateral inhibition and dominating topological projections between the layers, rather than by artificial computational heuristics. The network is structured as a two-layer lattice of neurons, corresponding to the major hippocampal areas. The lateral inhibition connections enhance the self-organising process.

The actor-critic model [19] most closely resembles the motivational, i.e. reward-related influence. At any discrete moment t, the user-specified keywords result normally in a big variety of options. A particular choice of an option is equivalent to an action on the Web environment. This corresponds to the choices of an actor. If the needed information is not available, the exploration of the chosen link is short, and the user does not branch off for other related links. This information is used as a feedback influence - the critic "criticises" the taken step. The actor-critic mechanism regards the actions of the user that are directed to finding particular targeted information.

The critic also adapts itself in correspondence with the actor. The reinforcement algorithm leads to improved behaviour with time, caused by the learning from the critic. The critic c at a given position l in the search space is as follows:

$$c(l) = \sum_i w_i f_i(l) , \tag{3}$$

where w_i is the weight between the current output from the episodic layer and the i-th location in the search space l. The critic learns the value function by updating the weights so that the prediction error that drives learning is reduced:

$$\delta(t) = R(t+1) + \gamma \cdot b(l(t+1)) - b(l(t)) \tag{4}$$

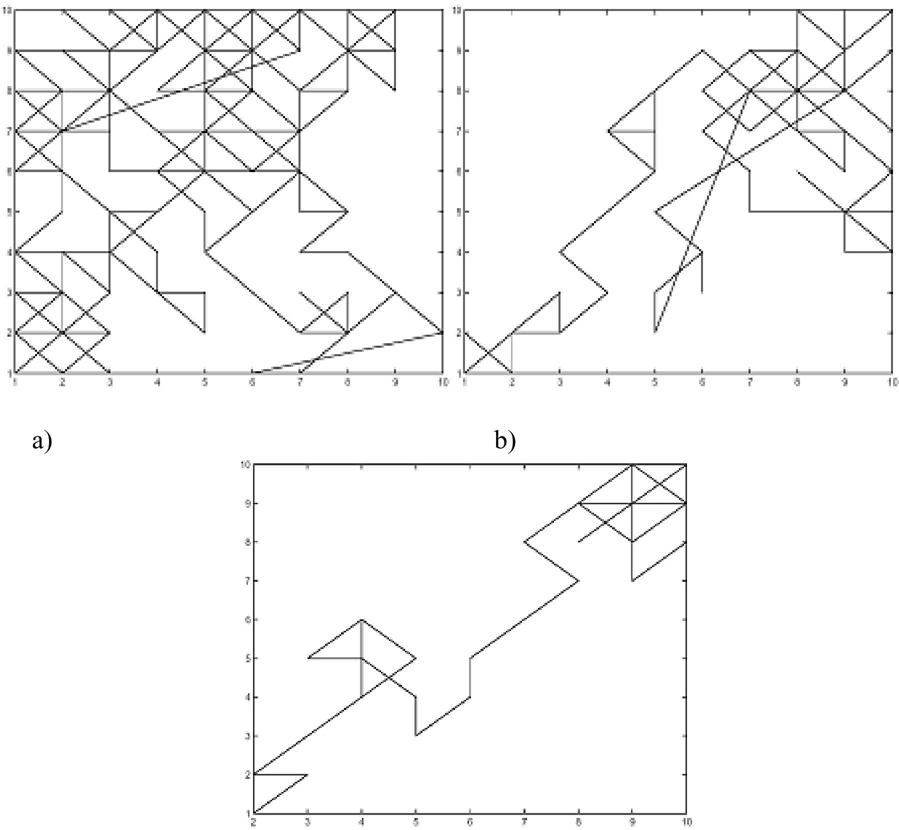
where γ is a constant discounting factor, set so that the weight between the output of the episode layer and the i-th location is minimum. R is the reward at moment t+1. The error is reduced by so changing the weights to the active locations on the search space to be proportional to:

$$\delta_t f_i(l) \tag{5}$$

In the experiments shown below, the actor makes use of k action cells a_j, $j = 1 \ldots k$. At position r, the activity of the each action cell is:

$$a_j(l) = \sum_i v_{ji} f_i(l)\,, \tag{6}$$

where a_j stays for the j-th action cell, and v is the adaptive weight between the action cell and the i-th output of the previous layer. The first step for the movement direction is taken randomly with a probability P_j. The next movement direction is typically chosen in random way. If there is a lateral connection to a related important to the user concept, the possibilities are restricted according to the choices made in the previous movements $P_j(t\text{-}1)$, $P_j(t\text{-}2)$, so that there is not a random walk, but smoother orbits with eventual sudden turns (Fig. 2).



a) b) c)

Fig. 2. Learned Web search paths by the actor-critic model for a single goal case; a) performance in the range 1-5 trials; b) performance in the range 75-80 trials; c) performance in the range 190-200 trials

The actor weights are adapted according to:

$$\Delta v_{ij} \propto \delta_t f_i(l_t) g_j(t), \tag{7}$$

where g reflects the previous-history restrictions on the search path. Fig. 2 depicts the optimisation of a search trajectory, which is only due to the learning of the critic. Finding a more meaningful search path is done by the learned episodes. The optimisation of the search path is guided by the learning of the critic (Fig. 3).

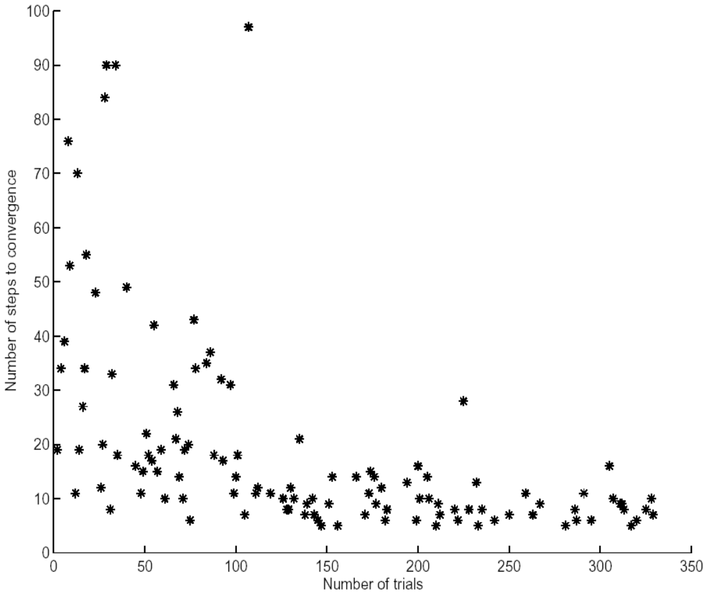


Fig. 3. Convergence rate averaged among 10 sets of 200 experiments

5 Designing Neuro-cognitive Web Interfaces

Among the many ambitious goals of the Web is to build agents/servlets/ applications/ interfaces that are self-explanatory, user-friendly, perceptually salient and conceptually understandable to *every* individual person [20], [21]. This gives confidence in applying the autobiographical agent approach to Web agent design, as at least in robotics, it has given promising and efficient results. In relation to this, an example from Web design is discussed, which is a focused example of the need for "vertical" re-categorisation of the "depth" of the individual user previous-history Web experience. Personalised Web systems [22] often employ "collaborative filtering" or user-similarity based ("horizontal") modelling principles, from the early works [23],

[24] to the numerous recent studies[1]. The cognitive/psychological motivation behind their definition of user interests, however, is vague. The discussed application has attempted to model short-term user interests. The results clearly show that before clustering user preferences based on most recent Web behaviour, the true "persona" has to be defined. The application in focus is called WebPersonae and is aimed to assist the user in browsing the Web [25], [26][2]. The authors have designed a search result reorderer along with the WebPersonae system. The basic goal of the reorderer is to introduce context-sensitivity to search engine results by estimating the user's current Persona and re-ranking the results to a query based on this Persona. As the user moves from page to page, the Personae recognition module identifies the current Persona. When the user runs a search to the Web, the system uses the most similar Persona[3]. to re-rank the received results - the most similar pages are ranked near the top of the list [26]. As the user browses from page to page, the system recalculates Personae similarities. In a sense, this system represents a "hippocampal" (pure "episodic") memory for the previous events/searches.

The evaluation of the search result reorder system has shown the encountered difficulties in user modelling by the autobiographical agent. The straightforward experiment reordered every set of results according to the similarity of each result to the current Persona. The current Persona was itself selected based on the user's recent browsing history. The second set of experiments was aimed at overcoming the 'naivete' of the initial approach. An 'omniscient' version of the system was designed for use with the test data only. This version implements an oracle or look-ahead module that can 'see into the future', i.e. it can look ahead and see which URL a user clicked on, and then select the Persona that *would have given* the best possible up-ranking to that result. This omniscient system is capable of producing a favourable re-ranking for approximately 95% of the search instances in the data-set. This shows that it is possible to give favourable re-rankings most of the time, providing the correct Persona is selected [26]. Being in process of development and evaluation, the WebPersonae system allows to make some conclusions about the nature of the "user-and-the-Web" interaction process as something more sophisticated than simply collections of sequences of events. What is required is a brain-like module, imitating the hippocampal-cortical relations in new knowledge acquisition, i.e. re-categorisation is needed to select the correct Persona. We propose to use our model for finer re-categorisation of user interests and "conceptual reasoning" via, for example, mapping perceptual to semantic cues [27].

The experiments with the interface have shown that the Personae appear intuitive and are adequate for representing different domains of interest. The weak link in the system, according to the authors, is the identification of "when" and "who" to help. The foreseen future improvements are to introduce a thesaurus component for identifying synonyms, and thus cluster based on concepts rather than just words, to employ hierarchical clustering by retaining the hierarchy of interests to represent broad and narrow topics and assist the user when different levels of detail are

[1] For example, Google returns 294 000 hits for "collaborative filtering", 30.06.2004

[2] We would like to thank Dr. Nicholas Kushmerick and JP McGowan from University College Dublin for sharing the ideas and the realisation of the WebPersonae interface

[3] TF-cosine similarity

required. The authors emphasize the necessity to create temporary Personae when the user's browsing session does not imply any of their long-term Personae. The temporary Personae can be updated incrementally as the user browses, and used to give short-term context sensitivity. When the user enters another Persona, these temporary ones can be deleted, or if their use continues, they can be made permanent, i.e. long-term [26]. The main aspect of the authors' analysis of the implemented system is the shift from "pure" computer science towards cognitive (neuro-) science approach to personalised Web agent design.

6 Conclusions

Psychological studies show that humans integrate and interpret new experiences on the basis of previous ones [8], [28], [29]. Autobiographical agents attempt similar behaviour on the basis of detailed knowledge of the neuro-cognitive processing mechanisms of new and old episodes in the brain. The paper argues that these mechanisms are needed in artificial/autonomous/intelligent agents to perform better and proposes to set this as an aim in building Web agents. It discusses a neurologically plausible model of episodic/event memory and its application in imitation of user Web behaviour. The autobiographical Web agents are needed to simplify the computational and time-consuming costs and to make the Web friendlier and more meaningful to the individual user.

Acknowledgement. This work is supported in part by TIC2000-1635-C04-04, TIC2000-0399-C02-01 of CICYT, Ministerio de Ciencia y Tecnologia of Spain, a Reseach Grant to Maya Dimitrova by CVC-UAB, 2004, and Contract No 809/98 of the National Research Fund, Bulgarian Ministry of Education and Science.

References

1. Petrie, C.J.: Agent-based engineering, the Web, and intelligence. IEEE Expert, Vol. 11:6, (1996), 24-29
2. Sloman, A., Chrisley, R.: More things than are dreamt of in your biology: Information processing in biologically-inspired robots. Proc. WGW'02 Workshop on Biologically-Inspired Robotics: The Legacy of W. Grey Walter, Hewlett Packard Research Labs, Bristol, August (2002), http://www.cs.bham.ac.uk/˜axs/, http://www.cs.bham.ac.uk/˜rlc/
3. Sloman, A.: AI's greatest trends and controversies. Edited by Haym Hirsh and Marti A. Hearst, IEEE Intelligent Systems and their Applications, Jan/Feb (2000) 8--17, http://www.computer.org/intelligent/ex2000/pdf/x1008.pdf
4. Triesch, J., Wieghardt, J., von der Malsburg, C., Mae, E.: Towards imitation learning of grasping movements by an autonomous robot. Lect. Notes Artif. Intell, 1739, (1999), 73-84
5. Lourens, T., Wurtz, R.P.: Extraction and matching of symbolic contour graphs, International Journal of Pattern Recognition and Artificial Intelligence, (2003)
6. Barakova, E., Lourens, T.: Novelty gated episodic memory formation for robot exploration. Proc. 2004 2nd IEEE International Conference on Intelligent Systems IS´2004, Varna, Bulgaria, Vol I, (2004), 116-121
7. Verschure, P.F.M.J., Voegtlin, T., Douglas, R.J.: Environmentally mediated synergy between perception and behaviour in mobile robots, Nature, Vol. 425, 9, (2003), 620-624

8. Conway, M.A.: Sensory-perceptual episodic memory and its context: autobiographical memory. Phil. Trans. R. Soc. Lond. B 356, (2001), 1375-1384
9. Benga, O., Miclea, M.: New trends in development and cognition. In: O. Benga, M. Miclea (eds.), Development and Cognition. Cluj University Press, Cluj-Napoca, ISBN 973 8095 82 4, (2001), 11-20
10. Dimitrova, M.: Cognitive modelling and Web search: Some heuristics and insights, Cognition, Brain, Behaviour, vol VII, 3, (2003), 251-258
11. Wood, E., Dudchenko P., and Eichenbaum, H.: The global record of memory in hippocampal neural activity. Nature, 397, (1999), 613-616
12. Jensen, O., Lisman, J.E.: Hippocampal CA3 region predicts memory sequences: accounting for the phase precession of place cells. Learning and Memory, 3, (1999), 279-287
13. Eichenbaum, H., Dudchenko, P., Wood, E., Shapiro, M., and Tanila, H.: The hippocampus, memory, and place cells: Is it spatial memory or a memory space? Neuron. Cell Press, (1999), Vol. 23, 209-226
14. Barakova E. and Lourens T.: Prediction of rapidly changing environmental dynamics for real time behavior adaptation using visual information. Workshop on Dynamic Perception, Bochum, Germany, Nov. (2002)
15. Piaget, J.: The Psychology of Intelligence, Routledge, Taylor & Francis, New York, (1950)
16. Sanger, T. D.: Theoretical considerations for the analysis of population coding in motor cortex. Neural Computation, 6, (1994), 29-37
17. Kohonen, T.: Self-organizing formation of topologically correct feature maps. Biological Cybernetics, 43, (1982), 59-69
18. Friske B.: Growing cell structures- a self-organizing network for unsupervised and supervised learning. Neural Networks, 7, (1995) 1441-1460
19. Sutton, R.S. and Barto, A.G.: Reinforcement Learning: An Introduction MIT Press, Cambridge, MA, (1998)
20. Lee, Tim Bernards, Fitting it all together, Invited talk at the WWW 2003 Conference, Budapest, Hungary, (2003)
21. Kushmerick, N., Gleaning answers from the web, Proc. AAAI Spring Symposium on Mining Answers from Texts and Knowledge Bases, Palo Alto, (2002), 43-45
22. Bonett, M.: Personalization of Web services: Opportunities and challenges, Ariadne, 28, 2001. [http://www.ariadne.ac.uk/issue28/personalization/]
23. Resnick, P., Iacovou, N., Suchak, M., Bergstrom, Riedl J.: GroupLens: An open architecture for collaborative filtering of netnews. Proceedings of ACM 1994 Conference on Computer Supported Cooperative Work, Chapel Hill, NC: ACM, (1994), 175-186.
24. Shardanand, U., Maes, P.: Social information filtering: Algorithms for automating "word of mouth". Proceedings of CHI'95 -- Human Factors in Computing Systems, (1995), 210-217
25. McGowan, J. P., Kushmerick, N., Smyth, B.: Who do you want to be today? Web Personae for personalised information access. *AH 2002*, (2002), 514-517
26. McGowan, J.P.: A Multiple Model Approach to Personalised Information Access. MSc thesis, University College Dublin, (2002)
27. Binefa, J., Sánchez, M., Vitrià, J., Radeva, P.: Linking visual cues and semantic terms under specific digital video domains, Journal of Visual Languages and Computing, Vol. 11, 3, (2000), 253-271
28. Tulving, E., Donaldson, W.: Organization of memory. New York: Academic Press, (1972)
29. Baddeley, A.D.: Human Memory: Theory and practice. Lawrence Erlbaum Associates, Hove, UK, (1990)