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EPIROME – A Novel Framework to Investigate High-Level Episodic Robot Memory*

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***Abstract*—Episodic memory has been examined in different disciplines such as psychology and neuroscience for more than 30 years. Now, engineering and computer science are developing an increasing interest in episodic memory for artificial systems. In this paper, we propose a novel framework referred to as EPIROME to develop and investigate high-level episodic memory mechanisms which can be used to model and compare episodic memories of high-level events for technical systems. We applied the framework in the domain of service robotics to enable our service robot TASER to collect autobiographical memories to improve action planning based on past experiences. The framework provides the robot with a life-long memory since past experiences can be stored and reloaded. In practise, one main advantage of our episodic memory is that it provides one-shot learning capabilities to our robot. This reduces the demerit of other learning strategies where learning takes too long when used with a real robot system in natural environments and therefore is not feasible.**

***Index Terms*—episodic memory, one-shot learning, life-long robot memory, service robotics.**

I. Introduction

The study of episodic memory began in the early 1970's when the psychologist Endel Tulving made a first distinction between episodic and semantic memory [1]. At that time it was defined in terms of materials and tasks. Tulving specified episodic memory (EM) as our experiences of certain, spatio-temporal definite episodes (e.g. your last vacation) and our general knowledge (language translations, facts like "upon Sunday follows Monday" *etc.*) as the semantic memory (SM). But his suggestions that episodic and semantic memory are two functionally different memory systems quickly became controversial. Caused by many criticisms, the episodic memory definition was subsequently refined and elaborated in terms of main ideas such as self, subjectively sensed time, and autonoetic consciousness.

Today episodic memory is seen as one of the major neurocognitive memory systems [2] that are defined in terms of their special functions (what the system does or produces) and properties (how they do it). It shares many features with semantic memory, out of which it grew, but it also possesses features that semantic memory does not [3]. Episodic memory is oriented towards the past in a way in which no other kind of memory system is. It is the only memory system that allows people to consciously re-experience their past. It has a special and unique relationship to time [4].

Neuropsychology took up the idea of episodic memory and tried to find proofs for the concept in biological systems. Many investigations of amnesic patients were carried out to locate the episodic memory. It was considered that the episodic memory is mainly related to the medial temporal lobe and hippocampal structures [5]. Especially the case of the patient H.M., who became the worlds most famous hippocampal amnesic, was of interest for neuroscience concerning memory research [6], [7].

Over the last decade, in engineering and computer science an increasing interest in episodic memory mechanisms can be noticed. In section II these research ambitions are discussed. However, first we must review the characteristics of episodic memory in human archetypes that evolve from psychology and neuroscience. Because psychology assumes the automatic memory formation in humans to be an obligatory process, it is not listed as a special characteristic below:

1) **Autonoetic:** Remembering episodic memory is characterised by a state of *awareness* unlike that in semantic memory, that is *noetic*. When one recollects an event autonoetically, one re-experiences aspects of a past experience. Re-experiencing of an already learnt episode is not necessary.
2) **Autobiographical:** The rememberer remembers an episode from his or her own perspective. There is no possibility to change the viewpoint in AI systems. To put oneself in someones place is the highest achievement of human intelligence. Moreover, there are studies proving that autobiographical and episodic memory are separate memory systems [8].
3) **Variable Duration:** The time period that is spanned by an episode is not fixed.
4) **Temporally Indexed:** The rememberer has a sense of the time at which the remembered episode occurred.
5) **Imperfect:** Our memory is incomplete and can have

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errors. New sensations are forced to satisfy already experienced concepts.
6) **Primed:** Recall occurs more quickly when it is primed by repetition, recall of related information, or similar states.
7) **Forgetting:** It is still not clear if there is forgetting in long-term memory (LTM), or rather problems of recall of the memory traces. Currently, mechanisms of *active forgetting* are discussed [9].
8) **Level of Activation:** Exposure frequency and recency affect the speed of probability of recall. It mainly describes the *primacy & recency effect* where the former is based on LTM effects and the latter is based on the contents of the working memory.

The remainder of the paper is structured as follows. After this brief introduction to episodic memory from the psychological and neuropsychological point of view, we present some related work in section II particularly from the field of engineering and computer science. In section III we present the domain of our multimodal service robot TASER. Our novel EPIROME framework is introduced in section IV. We will conclude with an outline of our future work in section V and give a general conclusion of our EPIROME framework and episodic memory in robotics in the last section VI.

II. Related Work

Mechanisms of episodic memory can be used to develop new learning algorithms and experience-based prediction systems. Agents that do not remember their past are bound to repeat both the previous mistakes and the reasoning efforts behind them. Thus, using an episodic memory helps to save time by remembering solutions to previously encountered problems and to anticipate undesirable states. In literature several important approaches to create episodic memory in artificial system are explored.

A. SOAR-EM

A framework for describing functional stages for computational models of episodic memory is presented in [10]. They realised the first implementations of a computational model of episodic memory in SOAR. SOAR is one of the major cognitive architectures based on production rules [11]. It has two types of knowledge, working memory (short-term, declarative) and production rules (long-term, procedural). Nuxoll & Laird demonstrated all four stages of their model (encoding, storage, retrieval and use) for a simple interactive task.

They developed a Pacman-like domain to wander around in a limited grid and collect the most food-points in the least amount of time. Their goal was for the agent to use its episodic memory in place of its knowledge about the food-points to aid in selecting the direction in which it should move.

An activation-based matching scheme leads to significantly better results than its unbiased match predecessor that was developed earlier. Furthermore, as the agent gains more memories, the eater's performance continues to improve until it performs comparably to the greedy eater (that only heads to the best food in its direct neighbourhood) [10].

B. Episodic-memory approach to the problem of pattern capture and recognition

Tecuci *et. al* simply depict the following characteristics as requirements for episodic memory. The memory organises temporally ordered events, these are dynamic (i.e. they change the status of the world) and they are observed incrementally. Capture and recognition of past events are the basic processes of an episodic memory [12]. An episode was defined as a sequence of actions with a common goal. Their main goal was to achieve a retrieval algorithm that can deal with incrementally available data to make predictions dynamically in a fast and accurate manner.

They evaluated their approach on a goal schema recognition task in the Linux Plan Corpus. The task was to predict the type of goal an agent (Linux user) has without exact parameters. Linux users were given a goal (e.g. find a file with "exe" extension) and were instructed to achieve it using simple Linux commands (no pipes *etc.*).

Even if they proved that memory retrieval is scalable, they achieved only the same level of performance as statistical approaches. Unfortunately, the system is not able to recognise subgoals of long period plans and it is sensitive to noise. A benefit of the system is the reduction of search space by only storing relevant episodes.

C. Neural models

An episodic memory model using spiking neurons was presented in [13]. They described a model that meets requirements for real-world robotics applications. Requirements were: (a) learn quickly and on-line, (b) recall patterns in their original order and with preserved timing information and (c) upon cueing, complete sequences from any position even in the presence of ambiguous transitions.

They proposed a two-layer feed-forward neural architecture based on SAM (spike accumulation and δ-modulation) neurons that is capable of categorising the continuous stream of sensorimotor patterns from a robotic system interacting with its environment. A learning-by-doing task was evaluated were the robot was taught to draw a circle by guiding its hand. By using a revised Hebbian temporal learning rule with synaptic history [13], the network took about 50 epochs to stabilise.

Unfortunately, the network is very sensitive to noise and the range of recorded episodes is very small. In our point of view this approach is not considered as episodic memory if it is at all related to nondeclarative procedural memory concerning the definition of LTM [5].

D. Memory retrieval through emotional salience and statistical information

Episodic memory retrieval driven by an emotional system of a humanoid robot was realised in [14]. A single episode is defined as a period of task execution of the robot during which the goal of the robot does not change.

The retrieval of episodes is accomplished through an algorithm that takes the current episode and selects several stored episodes for placement in the episodic memory-working memory set. The probability that a memory is relevant is calculated through the combination of two independent factors: a history component and a contextual component [15]. The retrieved episodes are used to generate future actions through a planning system. To represent and evaluate emotions they used Haikonen's system reactions theory of emotions (SRTE) as described in [16].

In their cognitive control experiment, the Agent ISAC (abbr. for Intelligent SoftArm Control) has to follow a moving object with its cameras. If a person yells "*Fire!*", ISAC uses attention, emotion and cognitive control, suspends the current tracking task and warns everyone to exit the room [17].

Unfortunately, ISAC recognises only four objects and four people in its semantic memory [14]. For the purposes of this experiment, episodes that were designed to use a variety of semantic memory units were hand-crafted. Tasks that could be solved cover subjects like placing objects in a certain configuration, greeting humans, and identifying objects.

Finally, it should be noted that the review of related work shows that engineering and computer science is in the early stages of episodic memory modelling. The presented approaches to building an episodic memory have the following problems:

- Only applicable in highly limited domains,
- in-appropriate to realise psychological functionality of episodic memory,
- only consideration of actions not of perceptual and executive information,
- mostly short sequences,
- one-shot learning seldom,
- gap of terminology of episodic memory among different disciplines.

III. The Multimodal Service Robot Platform

Since our research background belongs to the field of service robotics we developed a framework to investigate the use of episodic memory in real robot systems. The domain of service robotics is to assist human beings by performing jobs that are distant, auxiliary, dangerous or repetitive *etc*.

Westhoff *et. al* mention a novel concept for distributed programming of our multi-modal service robot TASER shown in Fig. 1 [18]. Furthermore, they are describing numerous practical experiments made with the robot. TASER has to work in a dynamic, real-world office environment and due to its mobility all the tasks slightly change. TASER is operated by a built-in control system, just driven by a Pentium IV 2.4 GHz standard computer. Due to TASER's evolution novel tasks may occur that can be solved in the analogical way of doing already learnt tasks. Thus, improved memory systems to remember previously encountered problems and to anticipate undesirable states are essential. Generalised memories of sequences consisting of action-based, perceptual and executive information can be applied to solve novel problems.

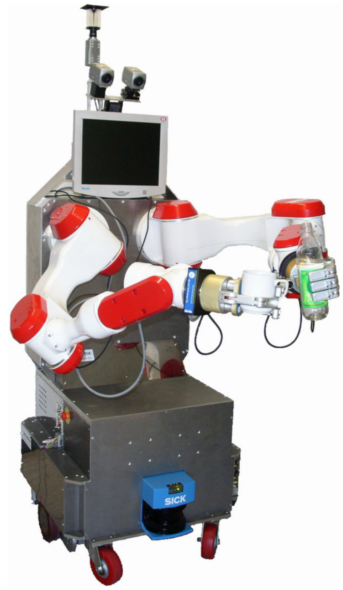

Fig. 1. The TAMS service robot TASER as research object for our high-level episodic robot memory system.

In the following we present some of the above-mentioned tasks. One of the high-level task is to e.g. "*water all flowers*". This means that TASER first has to pick up a watering can and refill it either in the kitchen, the rest room or at any other available water supply. Then the robot has to visit all offices, locate the flowers and pour some water into the flower tub. If an office is locked TASER has to go on with the remaining offices and can serve the locked one later.

Another example is as follows. To "*deliver a message to everyone of our group*" TASER has to carry the message, searching our floor for persons (e.g. detecting people by using face detectors) and hand-over or respectively tell the message to each person. Since the robot normally will not find persons in the server room, the episodic memory will help to optimise the task execution by suppressing to deliver something to someone in the server room.

Further tasks may have similar subsequences. If the robot should bring something from the laboratory to the kitchen or *vice versa* the subsequence (e.g. "*leave laboratory*", "*go to the hallway*", "*walk along hallway*", "*enter kitchen*", "*place in front of worktop*", "*put down object*") may be similarly independent of the object. These sequences can be generalised. In the case of "*water all flowers*" the task can vary from execution to execution caused by a dynamic environment and depending on which office may be locked or which flower tub maybe unreachable or hidden.

These examples show that computation of action sequences can be omitted if subsequences remain reasonably stable during different tasks. Memory retrieval can be used as heuristic to continue or stop the execution of a task. If the goal in a memory-based, predicted sequence is constantly

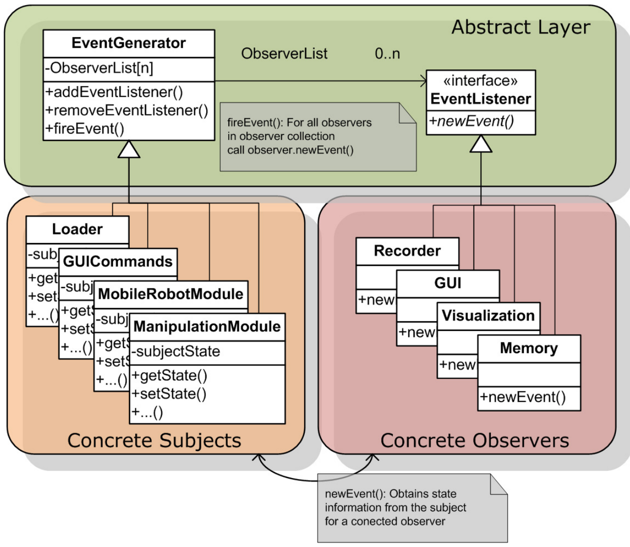

Fig. 2. The EPIROME architecture based on the observer design pattern. The lower left box shows event generating modules, whereas the lower right box depicts the modules listening to broadcasted events. The upper abstract layer specifies the interfaces for event broadcast capabilities.

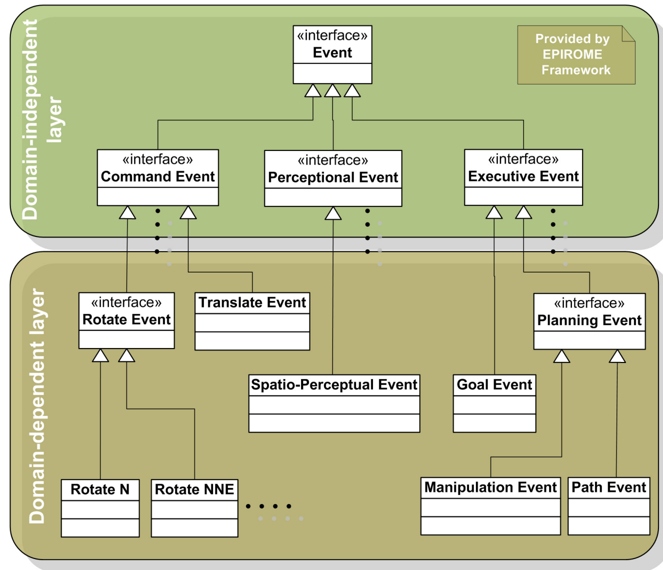

Fig. 3. The hierarchy of events. The classes and interfaces of the dependent layer are customised for our service robot domain. The episodic memory itself operates only on the independent event layer.

not reachable the robot should either be forced to use other approaches or to combine several subsequences of other less related memory traces to reach the goal (task decomposition).

IV. Framework Design

The EPIROME framework offers the capability to record high-level episodic memories as mentioned in section I, II and exemplified in section III. EPIROME is an independent framework that is based on the observer design pattern. The observer pattern is a design pattern for observing the state of an object in a program. It is mainly used to implement a distributed event handling system. The essence of the observer design pattern is that one or more objects (called observers or listeners) are registered (or register themselves) to *observe* an *event* which may be caused by the observed object (the subject) as depicted in Fig. 2.

The upper abstract layer in Fig. 2 is domain-independent and specifies the interface for event broadcast. The lower right box contains concrete observers. Each observer has to implement the method `newEvent()` and specify how to process the information of a connected subject if a new event occurs. Observers can be attached to concrete subjects by using `addEventListener()`. The lower left box of Fig. 2 contains concrete subjects (for our robot domain). Each subject extending the event generator has a list of observers listening to it. Each time a concrete subject perceive a specific event through the manifold sensors of the robot system, it will call `newEvent()` for all observers in its observer collection. Even if we described domain-dependant aspects in the two lower layers, they only illustrate how to use this kind of communication architecture. Such dependent units are easy to substitute to satisfy other domains.

In general we think of episodic memories as sequences of events. Each event carries time information and can be assigned to one of the three major event classes: perceptual events, command events and executive events (Fig. 3). Based on this domain-independent hierarchy, a more comprehensive classification can be applied to include domain-specific information. Fig. 3 shows a part of the event hierarchy realised for our service robot TASER. The processing within the memory module of our framework will only work on the domain-independent classification of events. Therefore, the framework can be applied to other domains seamlessly. In the following subsections we give a brief introduction on how we associate robotic events to the above-mentioned major event classes.

A. Perceptual events

This type of events focus on the recognition and interpretation of sensory stimuli. Perception obviously applies to all kind of sensoric modalities. In our robot domain, perceptual events are events that are perceived by the robot itself through its sensors. Perceptual events can be amongst others:

- **Spatial perceptual**: The robot has a sense where it is (e.g. laboratory, kitchen, office, *etc.*). Everytime the robot changes from one region to another it will receive a spatial event as e.g. "*I am in front of office c*" from its sensory system.
- **Stalled**: If the robot e.g. runs down a planned path and encounters a meanwhile closed door or an obstacle blocking its pathway it will receive an event signalising that he cannot pass through. In addition, manipulation events can also perceive if they get stuck.
- **Unimodal perceptual**: Perceptions can be based on a single sensor.
- **Multimodal perceptual**: Perceptions of e.g. objects can be combinations of different sensory information.

B. Command events

Command events are specifications of the ability to produce movements by interaction of a control unit and actuators. In case of TASER the control unit is the motor control system and the actuators are the servomotors. command events can be seen as basic movement functionality, typically: **Rotate**, **Translate**, **Stop**, **Open finger** *etc.*

C. Executive events

This category of events contains a kind of high-level abilities and meta events that amongst others can be seen as procedures. They are e.g. necessary for goal-directed behaviour. Thus they are called *executive functions*.

- **Goal**: An agent strives for a particular goal, this can be a high-level main task (e.g. "*bring me a coffee from the kitchen*", "*carry this bucket to the climbing robot*", "*water all flowers*") or a collection of subtasks (e.g. "*go to kitchen*", "*grasp bucket*").
- **Ends**: The agent confirms if a task/subtask is reached successfully or not. However, it also records if a goal is not reached to avoid the same mistakes next time.
- **Planning**: If the agent makes plans to solve tasks and desires (e.g. recharge, path planning)
- **Manipulate**: The ability to manipulate objects with e.g. a robot arm, hand.
- **Grasp**: The ability of using the robot hand. A subset of manipulation events.
- **Handle**: The combination of object grasping, manipulation, translation, *etc.*

It is obvious that the type of used tasks and events (e.g. spatio-temporal events like "*I am in the kitchen in front of the fridge*") makes our system operate on a high cognitive level. The current EPIROME framework for our robot domain possesses several observers and subjects. The user can choose between several basic command events to solve a desired task (Fig. 4). It has a visualisation tool to present experienced and currently running episodes to the user. Each event of an episode gets a dedicated colour depending on the event type (Fig. 4). This makes it easier for the user to make a first comparison of episodes visually. The map in Fig. 4 shows our hallway and the current position and sensing of our robot. The door application to the left of Fig. 4 is only used during simulation. Doors can randomly open or close to force the robot to stall and rearrange its path. This leads to considerable changes within episodes of the same task. As shown, the three episodes in the middle of the visualisation tool are of the same task and look similar, but the first episode differs from the other two after several events and is longer because the robot stalled due to a closed door. Nevertheless TASER solved its task successfully by replanning.

V. Future Work

The basic functionality of our framework for high-level episodic memory research in robotics is finished already. Our future work now is twofold.

Additional Modules: We will extend our system with further event generating modules. These components can be categorised to extend the already used perceptual, command and executive events. Thus, it will satisfy the current design. Additional event generating modules can be e.g. face detectors, manipulation units, object recogniser and locator *etc*. Additionally we are going to verify the approach proposed in [12]. Our framework can easily be extended and tested by using a module with their proposed capabilities as an additional event generating module. Thus we can compare our episodic memory module to the results of [12].

Storage & Retrieval: We are currently developing the memory module for episodic memory storage and retrieval capabilities. First, an on-line episode-to-episode and sub-episode comparison will be realised via a *Viterbi-algorithm*. The Viterbi-algorithm is a dynamic programming algorithm for finding the most likely sequence of hidden states – called the Viterbi path – that results in a sequence of observed events. The so-called *forward algorithm* is a closely related algorithm for computing the probability of a sequence of observed events. The results of the Viterbi-algorithm will be used as similarity measure for episode comparison. Based on the comparison we get potential memory traces to satisfy the current sensations. If the similarity is too small (below a threshold), the current episode will be stored as a new trace. This in particular depicts the important episodic memory characteristic of one-shot learning. Moreover, subsequences that occur often can be combined to a single trace. That means in our case, if the robot solves tasks in a new and distinct manner it will store a new memory trace immediately. Thus, an episode becomes a collection of several events in which frequently emerging subsequences can be generalised to a single abstract event within this episode. Consequently, the whole subsequence is not stored again and the generalised abstract event refers to the memory trace of the experience related to this subsequence[1]. Furthermore, the level of activation of a trace of a subsequence has to be primed depending on its occurrence.

Since we can easily add additional concrete observers to the EPIROME architecture it will be a cinch to compare different memory mechanisms implemented by different modules, listening to the same type of events.

VI. Conclusion

Nowadays, after dozens of years of psychological and neuropsychological research, episodic memory is finding its way into engineering and computer science. With the EPIROME framework that we developed, it is possible to model and compare episodic memories of high-level events for technical systems. We applied this framework to our robot system and it provides TASER with a life-long memory to improve action planning based on past experiences. Table I shows the characteristics of episodic memory that EPIROME already complies

[1] We appreciate that we have to take care about temporal indexing of each episode if we treat generalisation.

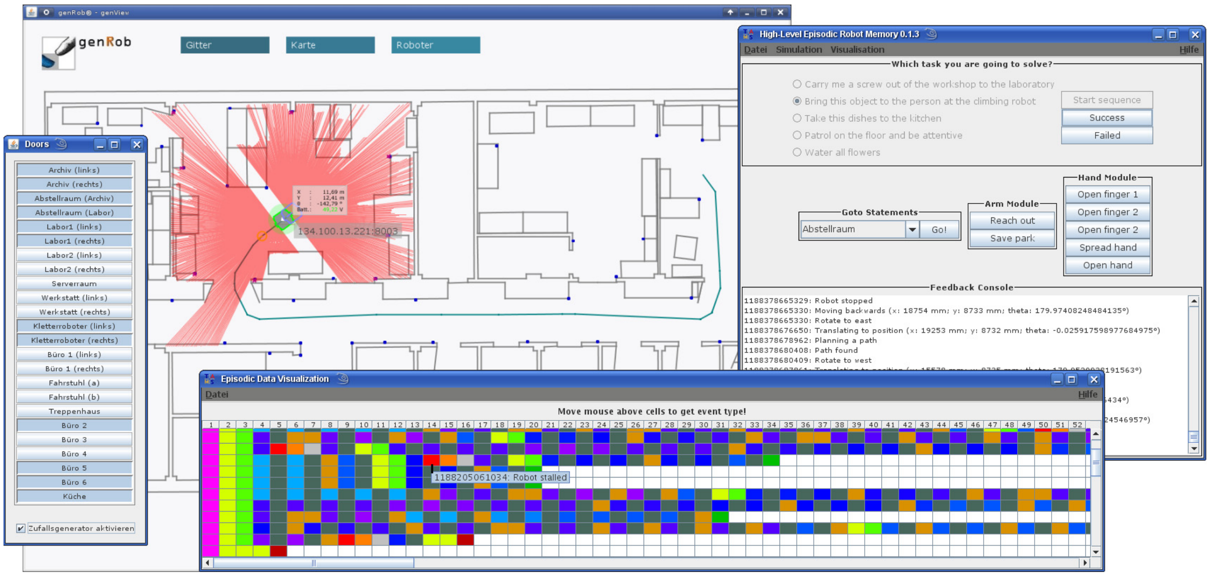

Fig. 4. Screenshot of the running EPIROME framework. The graphical EPIROME user and command interface on the right, at the bottom already recorded autobiographical sequences of our robot, the map of our hallway in the background and the randomised door control system.

Episodic Memory		EPIROME
Autonoetic	☑	Timely distinguishable sensations
Autobiographical	☑	Robots own sensations
Variable Duration	☑	Episodes bound by start / end event
Temporally Indexed	☑	Timestamps
Imperfect	☐	Error simulation / Sensor uncertainty
Primed	☐	Priming of frequently used episodes
Forgetting	☐	Deletion of less used sequences / Physical limited storage devices
Level of Activation	☐	Probabilities in retrieval function

TABLE I

ALREADY COMPLIED WITH CHARACTERISTICS (☑) OF EPISODIC MEMORY WITH THE CURRENT EPIROME FRAMEWORK AND OUR FUTURE WORK (☐).

with compared to the psychological and neuropsychological characteristics mentioned in section I. Unfulfilled conditions we depicted in section V about future work.

One main advantage of our episodic memory is that it provides one-shot learning capabilities to our robot. This is very important while it learns novel tasks. On the other hand, we are not simply processing motor information but also high-level sensory events which are mostly neglected or of low-level in artificial systems. If an episode based on current sensings does not reach a goal, already experienced episodes or subsequences of past episodes may provide approaches to finally achieve success. Our system aids in structuring high-level tasks into a well-composed hierarchy.

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