Towards an Episodic Memory for Cognitive Robots

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Abstract. Different disciplines such as psychology and neuroscience have been examining episodic memory (also referred to as declarative memory) for more than three decades. Now, engineering and computer science are developing an increasing interest in episodic memory for artificial systems. We propose a novel framework 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 demonstrate how we applied the framework to the domain of service robotics. High-level events emanate from basic skills, elementary operations, sequences of elementary operations, environmental changes and the detection of human interactions. The framework enables 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 disadvantage of other learning strategies where learning takes too long when used with a real robot system in natural environments and therefore is not feasible.

1 Introduction

Memory is central to the human condition and has been investigated at many levels. Neuroscientists have studied the molecular and cellular mechanisms of memory in animals and humans, and psychologists have contributed to our understanding about the different kinds of processes involved in memory through research with amnesic patients and normal subjects. Engelkamp [1] propose to distinguish memory systems based on the type of stored information (e.g. episodic-semantic, verbal-nonverbal-imaginal), the type of processes involved (e.g. declarative-procedural, implicit-explicit) and such memory systems based on the length of time that information is retained (e.g. short–term-long–term).

The study of episodic memory began in the early 1970s when the psychologist Endel Tulving made a first distinction between episodic and semantic memory [2]. At that time episodic memory (EM) was defined in terms of materials and tasks. Tulving specified episodic memory as your experiences of certain, spatio-temporal definite episodes (e.g. your last business trip) and our general knowledge (language translations, facts like “what is a pen” *et cetera.*) as the semantic memory (SM). However, his suggestion that episodic and semantic memory are two functionally different memory systems quickly became controversial. As a result of the criticism, the episodic memory definition was refined and elaborated in terms of its main ideas such as self, subjectively sensed time, and autonoetic consciousness. Today, episodic memory is seen as one of the major neurocognitive memory systems [3] that is defined in terms of its special functions (what the system does or produces) and its properties (how it does that). It shares many features with semantic memory, which it grew out of, but it also possesses features that semantic memory does not have [4]. 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 with time [5]. Neuropsychology took up the idea of episodic memory and tried to find proofs for the concept in biological systems. Tests on amnesic patients (e.g. the famous hippocampal amnesic H.M. [6, 7]) suggested that the episodic memory is mainly related to the medial temporal lobe and hippocampal structures [8].

The brain uses vast amounts of memory to create a model of the world. Everything a person knows and has learned is stored in this model. The brain uses this memory-based model to make continuous predictions of future events [9]. If those predictions are disproved, the brain learns (e.g. by novelty detection [10]), and adjusts its memories according to the new data. The memory seems to be organised in a hierarchy, each level beeing responsible for learning a small part of the overall model. Kanerva [11] proposed a *sparse distributed memory* (SDM) model that offers many of the characteristics that a human memory posseses. He also developed a mathematical model for this theory.

Over the last decade an increasing interest in episodic memory mechanisms can be noticed in engineering and computer science. In Section 2 these research ambitions are discussed. However, first we must review the characteristics of episodic memory in humans 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:** A person remembers an episode from his or her own perspective. There is no possibility to change the viewpoint in AI systems. To put oneself in someone else’s place is the highest achievement of human intelligence. Moreover, there are studies proving that autobiographical and episodic memory are separate memory systems [12].
3. **Variable Duration:** The time period that is spanned by an episode is not fixed.

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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 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 forgetting is a problem of actual information loss in long-term memory (LTM), or rather a problem of recall of the memory traces. Currently, mechanisms of *active forgetting* are being discussed [13].
8. **Level of Activation:** Exposure frequency and recency affect the speed and probability of recall. The level of activation 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.

This 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 2, particularly from the field of engineering and computer science. Section 3 describes the domain of our multimodal service robot TASER. Our novel EPIROME framework is introduced in Section 4. We conclude with an outline of our future work in Section 5 and give a general conclusion on our EPIROME framework and episodic memory in robotics in Section 6.

2 Literature Review – An Excerpt

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 by anticipating undesirable states. In literature several important approaches to creating episodic memory in artificial systems have been explored. Computational models of episodic memory can be devided into two categories: *abstract* an *biological*. Abstract models make claims about the "mental algorithms" that support recall and recognition judgments, without addressing how these algorithms might be implemented in the brain. Biological models make claims about the computation that support recall and recognition judgments, the main difference being that they also make specific claims about how the brain gives rise to these computations. While the former models account for challenging patterns of behavioural recall and recognition data from list learning paradigms, the brain-model mapping of the latter models provides an extra source of constraints on the model's behaviour. Even if Norman, Detre & Polyn [14] outline a comprehensive overview on computational models for episodic memory, only few robotic systems exist that make use of such models for learning.

2.1 Biological Models

2.1.1 Neural models

An episodic memory model using spiking neurons was presented in [15]. The author describes 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) complete sequences from any position even in the presence of ambiguous transitions upon cueing. The author proposes a two-layer feed-forward neural network architecture based on SAM (spike accumulation and δ-modulation) neurons that are 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 [15], the network took about 50 epochs to stabilise.

Regrettably, 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 rather than nondeclarative procedural memory according to the definition of LTM by [8].

2.1.2 Novelty mediated autobiographical memory

Barakova & Lourens [10] focus their research on memory-determined behaviour that relies on the neural mechanisms underlying episode formation. They use the term episodic memory as including event information within its temporal relatedness and directionality. They propose a computational model inspired by the hippocampal system of rats that aims at novelty-driven encoding and recall that facilitates inferential reuse of old memories [10].

Three neural structures are used to form a representation that is further used for navigation. Two simultaneous active neural networks, corresponding to the *Cornu Ammonis* 1 & 3 areas (CA1 and CA3) perform the major computations. The neurons in the CA3 area account for the temporal aspect and the formation of episodes. The representation in the CA1 area is prone to detect novelty. The third structure, *entorhinal cortex* (*EC*) provides the input patterns to both areas by projecting it onto CA1 and CA3 within a short time interval. Events that have been learnt as an episode will tend to be recalled together and after each other, even if the presentation order is changed [16].

Although the proposed model is one of the most biologically inspired robotics implementations of emergent behaviours based on episodic memory encoding, it relies mainly on spatial navigation tasks.

2.1.3 SMRITI

SMRITI is a computational model of episodic memory that illustrates the role of the hippocampal system in the acquisition, maintenance and retrieval of episodic memory, and proposes a detailed circuit-level explanation of how the hippocampal system realizes this function in concert with cortical representations. The model demonstrates how a cortically expressed transient pattern of rhythmic activity representing an event or a situation can be rapidly transformed into a persistent and robust memory trace as a result of long-term potentiation and long-term depression [17].

2.2 Abstract Models

2.2.1 MINERVA 2

MINERVA 2 [18] focus on schema abstraction, recognition, and frequency judgments and is best described as an existence proof: MINERVA 2 proves that it is possible to account for many aspects of memory for individual experiences (i.e., episodic memory) and memory for abstract concepts (i.e., generic or semantic memory) within a single system. MINERVA 2 does not prove that there is only a single system; rather, it proves it can be done.

In MINERVA 2, an item is represented as a vector of features in which each component is represented by the numbers 1, 0, or -1. Memory for an episode (e.g., for learning of a list of words) is a set of encoded vectors, with each event (word) being represented in a separate memory vector. The global similarity of a test item to a memory trace is determined by the sum of the product of each feature in a probe vector and the feature in the corresponding position in the memory trace vector divided by the number of features for which either the probe or the memory trace are nonzero. Accordingly MINERVA 2 has to compare a test item to all items in memory.

In this model each item will be stored in an continually growing matrix of memory traces. Together with the implausible presumption that a biological memory increases linearly, prototype and exemplar stimuli theory are not capable to model and explain human sensitivity to changing frequency of occurence and the influence of the sample size [19]. Adaptability to robotics seemed to be questionable.

2.2.2 An Episodic-memory approach to the problem of pattern capture and recognition

Tecuci *et. al* [20] simply outline the following characteristics as requirements for episodic memory: The memory organises temporally ordered events, that are dynamic (i.e., they change the status of the world) and are observed incrementally. Capture and recognition of past events are the basic processes of an episodic memory [20]. An episode is defined as a sequence of actions with a common goal. Their main goal is to achieve a retrieval algorithm that can deal with incrementally available data to make predictions dynamically in a fast and accurate manner. They evaluate 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.

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 is sensitive to noise. A benefit of the system is the reduction of search space by only storing relevant episodes.

2.2.3 SOAR-EM

Nuxoll & Laird extend the CBR paradigm by integrating episodic memory with a general cognitive architecture and developing task independent mechanisms for encoding, storing, and retrieving episodes [21]. They extend SOAR, one of the major cognitive architectures based on production rules [22]. SOAR has two types of knowledge, working memory (short-term, declarative) and production rules (long-term, procedural) and has been extended with episodic memory mechanisms into SOAR-EM.

In previous articles they propose 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. As the agent acquires more memory items, the eater's performance continues to improve until it performs at a level comparable to the greedy eater (that only heads to the best food in its direct neighbourhood) [23]. The hypotheses of cognitive capabilities resulting from this episodic memory are discussed and confirmed by implementations in their latest article [21].

2.2.4 LIDA

The *Learning* IDA (LIDA) architecture incorporates six major artificial intelligence software technologies: the copycat architecture, sparse distributed memory, pandemonium theory, the schema mechanism, the behavior net model, and the sub-sumption architecture [24]. LIDA is an extension for the Intelligent Distribution Agent (IDA) — which is a referred to as "conscious" software agent — by perceptual–, episodic–, and procedural–learning capabilities. It was created as model of human cognition that could be used to suggest possible answers to questions about the human mind. The authors designed and developed a practical application that could act like a human detailer, a person who negotiates with sailors about new jobs who are near the end of their current tours of duty.

A percept in the LIDA architecture can be thought of as a set of elements of an ontology that are relevant to the stimulus. They organise this information into a binary vector, where each field of one or more bits represents an element of the ontology [24]. A cue (the binary vector) will be used to query the content-addressable memories, autobiographical memory (ABM) and transient episodic memory (TEM). Both are based closely on Kanerva's sparse distributed memory (SDM) [25], as already mentioned in the Sec. 1. A similarity between SDM circuits and those of the cerebellar cortex are noted by [11]. Unfortunately, in this approach the whole domain must be specified within an ontology *ex ante*. It is limited to the domain of providing new jobs to sailors.

2.2.5 Memory retrieval through emotional salience and statistical information

Episodic memory retrieval driven by an emotional system of a humanoid robot is realised in [26]. 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 [27]. 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 [28]. In their cognitive control experiment, the Agent ISAC (Intelligent SoftArm Control) has to follow a moving object with its cameras. When a person yells "*Fire!*", ISAC uses attention, emotion and cognitive control to suspend the current tracking task and warns everyone to exit the room [29].

Unfortunately, ISAC recognises only four objects and four people in its semantic memory [26]. 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 are in the early stages of episodic memory modelling. The afore mentioned approaches should gave the reader an overview to current implementations of abstract and biological models of episodic memories in technical systems. For the majority the portability to the domain of robotics appears to be quite problematic. The presented approaches to build an episodic memory have the following problems in common:

- Only applicable in highly limited domains,
- inappropriate for realising higher psychological functionality of episodic memory,
- only consider actions, no perceptual and executive information,
- mostly handle short sequences,
- do not use one-shot learning,
- exhibit gap of terminology of episodic memory among different disciplines.

In addition to these problems, neuroscience revealed considerable evidence that attentional resources are necessary for the encoding of episodic memories, while the nature of the relationship between attention and neural correlates of encoding is unclear [30]. Especially a middle layer between encoding of sensoric stimuli from robot sensors to biological paradigms and high level learning, reasoning and prediction techniques are still missing to move the field of biological plausible computing. The findings offered by neuroscience research should be taken seriously and greater concentration should be given to dynamic network architectures that can alter their structure based on experience. Finally, a more comprehensive understanding of the brain and the central nervous system is critical to achieving better and biologically inspired adaptive computing systems.

3 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 involve long distances, are auxiliary, dangerous or repetitive *et cetera*.

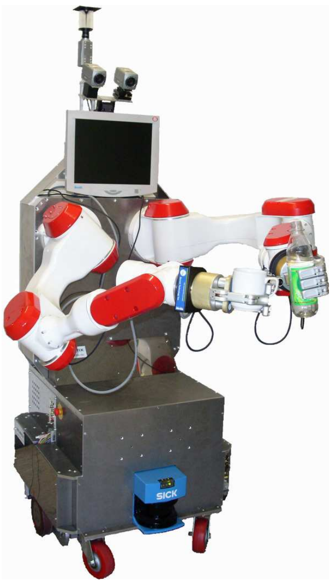

Figure 1. The TAMS service robot TASER as research object for our high-level episodic robot memory system.

Westhoff *et. al* mention a novel concept for distributed programming of our multi-modal service robot TASER shown in Fig. 1 [31]. Furthermore, they describe numerous practical experiments carried out on the robot. TASER has to work in a dynamic, real-world office environment and due to its mobility every execution of a task slightly changes. TASER is operated by a built-in control system, driven by one Pentium IV 2.4 GHz standard computer. Due to TASER's evolution novel tasks may occur that can be solved in analogy with 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 solving novel problems.

One such task as mentioned above can be described as follows. A high-level service robotic task is e.g. to "*serve drinks to guests*". For this task TASER has to pick up some drinks and glasses in the kitchen. Since the robot does not know where the guests are, it has to walk around to find them. If TASER finds somebody it has to evaluate if the person is an employee or a guest/foreigner e.g. by comparing known and unknown faces via a face detector. If a stranger/guest is detected, TASER offers a drink to him/her. Since only a couple of rooms are of special interest for guests on a visit (e.g. laboratory, climbing robot room, hallway, *et cetera*), an episodic memory of past, similar experiences will help TASER to realise that it has to search for strangers most frequently in these few rooms. This ensures that the quality and speed of TASER's service is improved.

High-level tasks may have similar subsequences. If the robot should bring something from the elevator to the workshop or *vice versa* the subsequence (e.g. "*call for the elevator*", "*enter elevator*", "*pick up object*" or "*walk along hallway*", "*enter workshop*", "*place next to worktop*", "*put down object on worktop*") may be similarly independent of the object. These sequences can be generalised. In the case of "*empty all waste bins*" the task vary among concrete executions caused by a dynamic environment and depending on which room may be locked or which waste bin may be unreachable or hidden. These examples show that generation of action sequences can be omitted if subsequences remain reasonably stable during different tasks. Memory retrieval can be used as heuristics to continue or stop the execution of a task. If the goal in a memory-based, predicted sequence is constantly 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. This can be seen as task decomposition.

4 The EPIROME Framework Design

The EPIROME framework offers the capability to record high-level episodic memories as mentioned in Section 1, 2 and exemplified in Section 3. 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 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). A domain-independent abstract layer specifies the interface for event broadcast. Observers can be attached to concrete subjects by using a connection method. Observers have to implement a method `newEvent()` offered by the abstract interface layer to specify how to process information on a connected subject if a new event occurs. Each subject has a list of observers listening to it. Each time a concrete subject perceives a specific event through the manifold sensors of the robot system, it will call `newEvent()` for all observers in its observer collection.

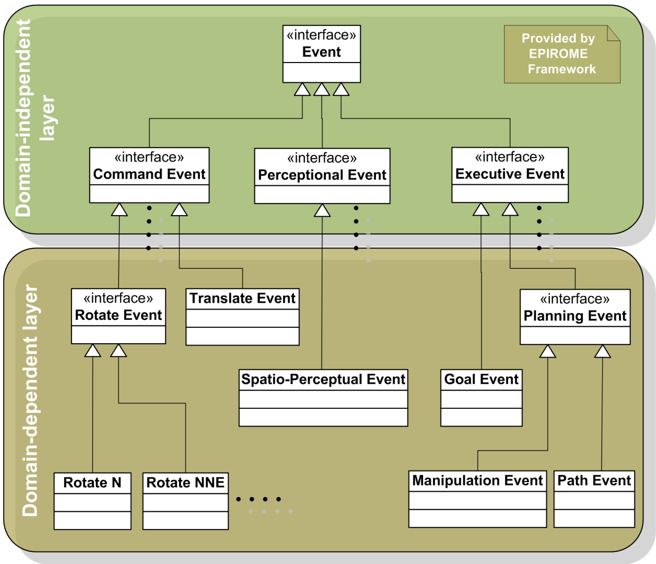

Figure 2. The hierarchy of events. The classes and interfaces of the dependent layer are customised for our service robot domain. The episodic memory itself operates only on the independent event layer.

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. 2). Based on this domain-independent hierarchy, a more comprehensive classification can be applied to include domain-specific information. Fig. 2 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 for 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.

4.1 Perceptual events

This type of events focus on the recognition and interpretation of sensory stimuli. Perception obviously applies to all sensoric modalities. Robot sensor input gets a high-level interpretation e.g. by mapping to semantic knowledge provided by a regionally labeled site map, basic physics rules *et cetera*. The following examples illustrate how high-level events emerge from low-level sensor data:

- **Spatial perceptual**: In this architecture we assume an inference component is capable of infering robots position relative to landmarks in a given semantically, regionally labeled site map. Everytime the robot changes from one region to another it will receive a spatial event as e.g. "*I am in front of the laboratory*". Based on this map and the localisation the robot has a *sense* where it is (e.g. laboratory, kitchen, office, *et cetera*).
- **Stalled**: If the robot e.g. passes down a planned path and encounters a meanwhile closed door or an obstacle blocking its way, it will receive an event signalising that it cannot pass through. In addition, manipulation events can also perceive if they get stuck.
- **Uni-/Multimodal perceptual**: Perceptions can be based on a single sensor or can be combinations of different sensory information. This information is useful for investigations to multimodal cognitive processing.

4.2 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 functionalities, typically: **Rotate**, **Translate**, **Stop**, **Open finger** *et cetera*.

4.3 Executive events

This category contains high-level abilities and meta events that are mostly reflective or procedural. They are 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 object to person X*", "*empty all waste bins*") or a collection of subtasks (e.g. "*go to kitchen*", "*grasp waste bin*"). This may result from direct user interaction.
- **Ends**: The agent confirms if a task/subtask is reached successfully or not. This also can be a result from feedback of a user. 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, trajectory planning)
- **Manipulate/Grasp**: The ability to manipulate/grasp objects with e.g. a robot arm, a hand.
- **Handle**: A more complex combination of object grasping, manipulation, translation, *et cetera* as combination of few basic command events.

The type of used tasks and events (e.g. spatio-temporal events like "*I am in the laboratory next to a desk*") demonstrates that our system operates 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. 3). It has a visualisation tool to present experienced and currently running episodes to the user [4]. Each event of an episode gets a dedicated colour depending on the event type (Fig. 3). The colour coding makes it easier to make a first comparison of episodes visually. The map in Fig. 3 shows a hallway and the current position and sensing of the robot. The door application to the right of Fig. 3 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. The three episodes in the middle of the visualisation tool are of the same task and look similar. However, the first episode differs from the other two after few events and is longer although the robot stalled due to a closed door. Nevertheless TASER solved its task successfully by replanning.

[4] A recorded sequence may look as follows (timecodes are not listed): GOALEVENT: Bring newly delivered material from the elevator to the workshop $\succ$ Floor in front of elevator $\succ$ Approach bucket $\succ$ Grasp $\succ$ Pick up bucket $\succ$ Bucket lifted $\succ$ Planning a path $\succ$ Path found $\succ$ Rotate to north north east $\succ$ Translating to position (x: 14303 mm; y: 7765 mm; theta: 45.117) $\succ$ Floor in front of lab $\succ$ Rotate to east $\succ$ Translating to position (x: 23646 mm; y: 8245 mm; theta: 0.0) $\succ$ Floor in front of office 2 $\succ$ Floor in front of office 3 $\succ$ Floor in front of office 4 $\succ$ Rotate to north east $\succ$ Translating to position (x: 26121 mm; y: 14523 mm; theta: 167.354) $\succ$ Workshop $\succ$ Put down bucket $\succ$ Bucket released $\succ$ Goal successfully accomplished . The majority of events can be deconvolved from complex to atomic actions.

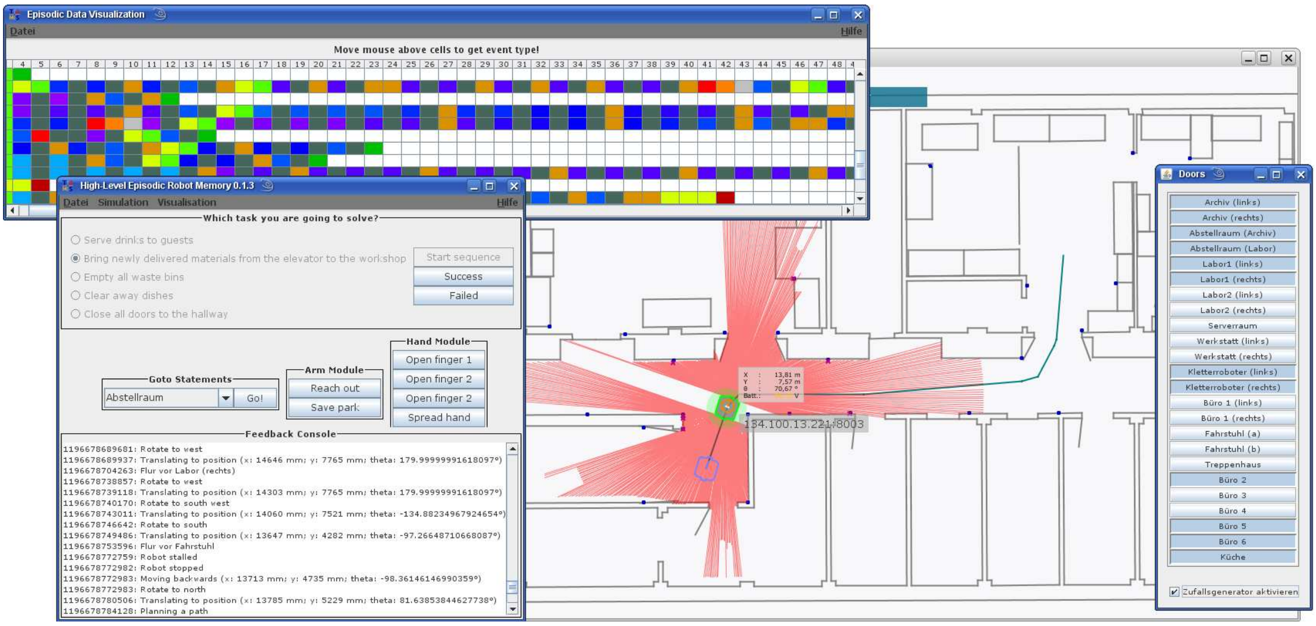

Figure 3. Screenshot of the running EPIROME framework. The graphical EPIROME user and command interface at the left, at the top already recorded autobiographical sequences of our robot, the map of our hallway in the background and the randomised door control system.

5 Current Work

The basic functionality of our framework for high-level episodic memory research in robotics has been completed. We already developed the EPIROME framework to collect high-level events and developed mechanisms to maintain such high-level events. These events are based on different modules that provide particular high-level information, e.g. the path planner provides information like "*move straight on for distance Y*", "*turn right*", "*turn hard left*", *et cetera*; events might be given *apriori* by user interaction and commands; an open or closed door can be sensed through the laser-range scanners in combination with a site map; high-level arm movements like beckoning, opening a door, grasping an object on a table, shaking hands has been learned via a content-addressable SDM and can be recognised[5].

Our current work is twofold. First we 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 *et cetera*. Additionally we are going to verify the episodic memory approach to the problem of pattern capture and recognition through a goal schema recognition task in the Linux Plan Corpus proposed in [20] and compare it to our episodic memory module. Our framework can easily be extended and tested by designing a module with the capabilities proposed by [20].

And secondly, we are transferring and extending the SDM mechanisms that are already used for our manipulator unit to a more generalised memory that combines further robot sensors and actuators. If the robot solves tasks in a new and distinct manner, it will store a new memory trace immediately. Since the mathematical model of SDM follows the basic idea that the distances between concepts in human minds correspond to the distances between points of a high-dimensional space, we expect to get clusters of similar actions and action sequence concepts. Since our manipulator has proved to work well with an SDM, the main problem remains of how to convey the different types of features (based on the sensors) into the high-dimensional input vector required by the SDM. This encoding problem remains to be the major problem in associative-memories of which episodic memory and sparse distributed memory are parts.

At a later step, frequently emerging subsequences within episodes can be generalised to a single abstract meta event. Consequently, individual subsequences are not stored redundantely and the generalised abstract event refers to the memory trace of the experience related to this subsequence. This is consistent with the theory that related concepts are stored close together[6]. 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.

6 Conclusion

After three decades of psychological and neuropsychological research, episodic memory is finding its way into engineering and computer science. In this paper we gave an overview to current computational models of episodic memories and outline the problems of portability into robotics. Even for neuroscience the relationship between attention and neural correlates of encoding in episodic memory remains unclear. A better understanding of the encoding of sensoric stimuli from robot sensors to biological paradigms and high-level learning, reasoning and prediction techniques is necessary. We propose that findings offered by neuroscience and psychological research should be taken seriously to get a more comprehensive under-

[5] In addition the SDM stores a model of the world (concerning the manipulator) while the sensory information at a particular moment is represented as a vector of features (joint angles, tool-center-point & orientation) and a sequence of such vectors represent the passage of time. This has prediction capabilities since after short training the SDM returns predictions of some next arm positions that were normally activated from the current position.

[6] We are aware that we have to take temporal indexing of each episode into account if we use generalisation.

standing of the brain and the central nervous system, especially for advanced biologically inspired robotics. Close interdisciplinary work will be indispensable in reaching this major goal.

With our EPIROME framework it is possible to model and compare episodic memories of high-level events for technical systems. We apply this framework to our robot system and it provides TASER with a life-long memory to improve action planning based on past experiences. Table 1 shows the characteristics of episodic memory that EPIROME already complies in comparision to the psychological and neuropsychological characteristics mentioned in Tab. 1. Unfulfilled conditions are marked with □ in Tab. 1 and have to be discussed before implementing, e.g. it is eligible to realise forgetting as long as no physical storage or processing limitaion exist.

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 1. Characteristics of episodic memory of the current EPIROME framework (☑) and future work (□).

One major 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. Furthermore, by using an SDM, less used executive manipulation tasks will be forgotten. We are not simply processing motor information but also high-level sensory events which are mostly neglected or of low-level in other 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 achieving success. The system structures high-level tasks into a well-composed hierarchy. The EPIROME framework is a sophisticated model to establish human-like learning in AI robot systems and for investigating multimodal cognitive processes.

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