ART neural network-based integration of episodic memory and semantic memory for task planning for robots

Jauwairia Nasir[1] · Deok-Hwa Kim[1] · Jong-Hwan Kim[1]

Abstract

Automated task planning for robots faces great challenges in that the sequences of events needed for a particular task are mostly required to be hard-coded. This can be a cumbersome process, especially, when the user wants a robot to learn a large number of similar tasks with different objects that are semantically related. We propose a novel approach of user preference-based integrated multi-memory model (pMM-ART). This approach focuses on exploiting a semantic hierarchy of objects alongside an episodic memory for enhancing the behavior of an autonomous agent. We analyze the functioning principle of the proposed model by teaching it a few distinct domestic tasks and observe that it is able to carry out a large number of similar tasks based on the semantic similarities between learned objects. We also demonstrate, via experiments using Mybot, our ability to reach those goals that are not possible without the integration of semantic knowledge with episodic memory.

Keywords Adaptive resonance theory · Task planning · Cognition · Semantic memory · Episodic memory · User preference

1 Introduction

As the research output in autonomous robotics is increasing, we have seen considerable amounts of efforts being put into improving various functions that are expected from a fully independent robot. Technologies are continuously being developed for autonomous agents to improve their abilities to perceive the environment, to navigate through it, to manipulate objects, and to make appropriate decisions. For being able to perceive and infer its environment, an autonomous agent needs cognitive skills. These skills define the ability to acquire, learn and comprehend knowledge; reason and solve problems; and make decisions (Kim et al. 2013).

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s10514-019-09868-x) contains supplementary material, which is available to authorized users.

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The two types of declarative memories, episodic memory and semantic memory, are considered to play a significant role in cognition related problems (Irish et al. 2013; McRae and Jones 2013; Nuxoll and Laird 2007; Tulving 1972, 1983, 2002). The memory of personal experiences and specific events in time in a serial form is referred to as episodic memory whereas semantic memory is a structural record of facts, meanings and concepts that have been acquired over time (Tulving 1972, 1983, 2002). Episodic memory does not only allow us to learn spatio-temporal sequences of events but also allows us to extract regularities in the original experience and combine it with current knowledge (Nuxoll and Laird 2007). Similarly, concepts that form a part of semantic memory are also regarded as fundamental elements of almost all aspects of human cognition (McRae and Jones 2013). This knowledge is used by us to understand and recognize entities in our environment and use them to perform functions (McRae and Jones 2013).

The latest research has pointed out an overlap between the two types of memory systems demonstrating the interdependence of episodic memory and semantic memory on each other (Greenberg et al. 2015; Irish et al. 2013; Levine et al. 2004). The degree to which both memory systems depend on each other varies across theorists but there is a wider agreement upon the existence of interdependence. Episodic memory facilitates the formation of new semantic memories over time, while semantic memory can help in acquiring new episodic memories (Greenberg et al. 2015).

Having highlighted the important role episodic memory can play in task planning, it is necessary to mention that for teaching a robot various tasks using episodic memory, a user would have to either hard-code or teach, via learning from demonstration, the sequences of events for each predefined scenario. For example, for carrying out the task of *Move Apples from Counter to Fridge*, the robot will have to learn a sequence of events such as *Move to Counter*, *Pick up an Apple*, *Move to Fridge with the Apple*, etc. This method itself is not very flexible because each time it is required for the robot to perform a new task, manual amendments of source code would be needed even for a new task with only differences in the information about the objects involved. In this case, a semantic representation of objects can play a role to extend the learned experiences in order to perform similar tasks (*Move Oranges from Counter to Cupboard*) instead of learning them from scratch. In other words, there is a need for a mechanism that can develop relations between the concepts robots learn from their experiences and categories of semantically-related objects according to how the user wants to define the categories. Also, the relation between various semantically related categories is useful knowledge that can be used as leverage to help robots improve their reasoning capability. To the best of our knowledge, not much work (more on this in the next section) has been done to integrate the two types of memories to improve the decision-making abilities of agents in task planning scenarios.

Following this, we propose an adaptive resonance theory (ART) (Carpenter and Grossberg 1987) based integrated multi-memory neural model (pMM-ART) whose contributions, briefly, include: (1) introduction of an object fact map (OFM), (2) integration of OFM with an existing episodic memory, namely, pDM-ART (Nasir et al. 2018), and (3) an inference mechanism based on this integration. In more detail, the proposed model makes the following contributions:

1. Introduces a semantic knowledge base (**OFM**) that has the ability to interact with an episodic memory without an independent control module.
2. Introduces a mechanism for the **integration of OFM with an episodic memory**. The OFM and this integration give us the knowledge about how far in space the object categories are to each other with respect to attributes and the concepts they share, respectively. This knowledge is in terms of weighted connections.
3. Introduces an **inference mechanism** that makes use of the weighted connections to extend past experiences to plan for new similar tasks.
   – The model is able to extend its knowledge of planning a task to an entire category of objects by learning to plan for only one object from the category. For example, if through episodic memory, the model has learned the sequence of events for the task *Move Apple from Counter to Fridge*, then through integration of episodic memory and OFM, the model can predict the sequence of events for *Move Orange from Table to Cupboard* since *apple, orange*; *table, counter*; and *cupboard, fridge* are semantically related to each other.
   – Not only is the extension possible to the category the object belongs to but also to other similar categories.
   – The model is able to recognize an erroneous category of objects that arrives in a retrieval cue.

Section 2 presents related work, while OFM is discussed in Sect. 3. Section 4 discusses encoding and learning of tasks/episodes, while Sect. 5 demonstrates retrieval, memory consolidation process, and the formation of weights (1) between semantic concepts and object categories and (2) among object categories. Section 7 demonstrates the functioning principle of our approach in a simulation test-bed while Sect. 8 includes experimental results on Mybot. Lastly, concluding remarks follow in Sect. 9.

2 Related work

For enhancing the autonomous abilities of robots, various cognitive architectures have been proposed over the years (Benjamin et al. 2004; Carpenter et al. 1991; Carpenter and Grossberg 1987; Laird et al. 1987; Nuxoll and Laird 2007, 2012; Shapiro and Bona 2009; Stachowicz and Kruijff 2012). In Nuxoll and Laird (2007), Nuxoll and Laird defined the design space for episodic memory and provided its implementation in the Soar cognitive architecture (Laird et al. 1987) to extend the case-based reasoning paradigm. In ELM (Stachowicz and Kruijff 2012), an R-Tree is used to improve the retrieval accuracy for events that are defined and categorized on the basis of their type. This framework also allows the events to be overlapped, nested, and to form partonomic hierarchies.

In contrast to symbolic models for episodic memory, bio-inspired models try to categorize the events in a more efficient manner in that they allow the robots to encode, learn, and recall directly from the situations experienced by them (Hawkins et al. 2009; Hochreiter and Schmidhuber 1997; Starzyk and He 2007, 2009; Wang and Arbib 1990; Wang and Yuwono 1995; Wang 1999). Carpenter and Grossberg proposed ART Networks (Carpenter and Grossberg 1987) for the purpose of solving the constraint of stability–plasticity dilemma (Mermillod et al. 2013) for artificial neural networks. Among others (Taylor et al. 2009; Tscherepanow 2010; Tscherepanow et al. 2012), an episodic memory adaptive resonance theory model (EM-ART) (Wang et al. 2012a) seems promising due to its ability to store the spatio-temporal relations between events and then retrieve them at a higher tolerance towards noise in contrast to prior models. EM-ART has been extended to cater for repetition and user preference by Nasir et al. Nasir et al. (2018), which helps improve retrieval accuracy.

A considerable number of models with various architectures and designs to represent semantic knowledge have also been proposed to improve the reasoning and inferring abilities of autonomous agents (Al-Moadhen et al. 2013; Dayoub et al. 2010; Galindo et al. 2008; Ji et al. 2012; Rogers and Christensen 2013; Veiga et al. 2016; Wu et al. 2014). Galindo et al. (2008) introduced semantic maps that integrate semantic knowledge with hierarchical spatial information to assist in task planning by enriching the planning domain and reach those goals that are otherwise not achievable without including semantic knowledge. Wu et al. (2014) designed a model 10 based on a conditional random field that labels a segmentation tree with hierarchical semantic labels to improve reasoning skills of robots while planning tasks. Also, Veiga et al. (2016) provided a unified framework consisting of object perception, semantic map, and decision-making for an efficient search for objects in a domestic environment.

Among bio-inspired models, a few of them have integrated semantic memory and/or memory consolidation processes along with the episodic memory models (Gao and Tan 2014; Wang et al. 2012b, 2017). Gao and Tan provided a method to encode the daily activity patterns in episodic memory EM-ART. The regularities in these activity patterns are extracted to consolidate patterns into semantic memory (Gao and Tan 2014). Wang et al. (2012b) integrated EM-ART employing Fusion ARTs with semantic and procedural memory modules. The semantic knowledge is built through a memory consolidation process in which episodes from the episodic memory are played-back to gradually extract and learn general facts by using a lower template matching threshold. More recent work by Wang et al. (2017) aims at building a framework that allows for interaction between episodic, semantic, and procedural memories without having an explicit control module and a generalized representation scheme for various forms of semantic knowledge. The last two approaches are similar to our work in the sense that they too integrate multiple memory modules to enhance autonomy. However, some of the ways in which our architecture differs are: (1) the definition of the semantic memory that forms by the consolidation process, (2) the consolidation process itself, and (3) the interaction between episodic and semantic memory.

Tan et al. (2010) incorporated reinforcement learning with the features of belief, desire, and intention in their fusion ART architecture that is able to refine plans without depending on the rigid user-defined paths enabling a robust performance. In Subagdja and Tan (2012), the authors proposed iFALCON, an architecture based on ART that is able to plan on the fly in situations when the required knowledge is insufficient. It does this by using a new representation technique called 'gradient encoding'. These approaches are similar to our work in regard to that they aim to generate novel plans online; however, they differ in terms of architecture, methodology, and outcome. In addition, the definition of novel plans varies across the three models.

Following is a summary of the proposed approach:

- It utilizes pDM-ART (Nasir et al. 2018), an extension of EM-ART (Wang et al. 2012a), as the episodic memory. Proposed by Nasir et al. this episodic memory "helps frequent and significant episodes in undergoing consolidation-like process to form more stable memories which represent a concept of doing a particular task". The motivation to use pDM-ART in our proposed model is based on the fact that it caters for repetition and user preference at encoding. This leads to the development of semantic-like concepts during the retrieval process. These semantic-like concepts constitute consolidated memory. However, pDM-ART on its own, without integrating with a semantic knowledge base, can only recall sequence of events for those tasks that have been explicitly taught to the system.
- In pMM-ART, an OFM is constructed by encoding each unique object using a Fusion ART (Tan et al. 2007) and then grouping together the semantically related objects into object categories by making use of another Fusion ART. Weighted connections develop among object categories. These connections define the relationship between the categories based on the attributes they share.
- During the retrieval of learned episodic memories from the episodic or consolidated memory, top-down weighted connections develop between the semantic-like concepts and the activated object categories. These connections define the relationship between the object categories based on the concepts they share.
- These two types of weights can then be utilized to recall a sequence of events for those tasks that have not been explicitly taught to the system. These tasks differ in the information related to the objects involved in the tasks. An inference module makes use of the weighted connections to decide the most suitable plan in a given situation. Figure 1 highlights pMM-ART's basic architecture.

The approach presented in this paper seems to have some conceptual similarity with the widely known case-based reasoning (CBR) approach (Riesbeck and Schank 1989). Both

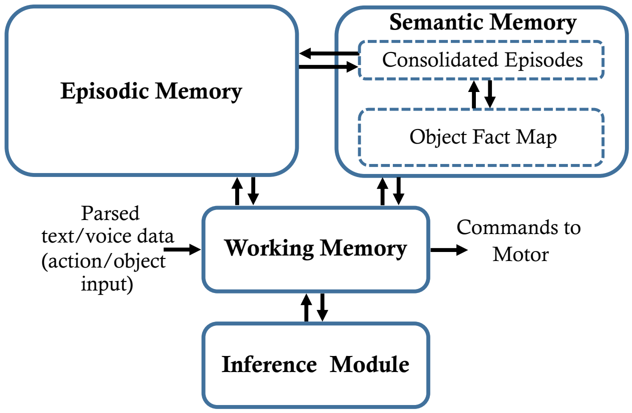

Fig. 1 Basic architecture of the proposed pMM-ART

methods solve new problems by adapting solutions that were used to solve old problems. While CBR may need human intervention for adaptation (Cunningham 1998), the proposed method tries to minimize this by integrating a semantic knowledge base. However, it has its limitations, which are discussed in the last section. For our simulations, we assume that the sensory data at the input of our system and the motor commands at the output are sufficient enough for our purpose. For the purpose of a proof of concept, we also demonstrate our model using a hardware architecture in Sect. 9.

3 Encoding, learning and retrieval of object categories

In this section, encoding, learning and retrieval of object categories is presented. As our entire architecture is based on hierarchical multi-channel Fusion ART neural networks (Tan et al. 2007), we begin by describing the dynamics of Fusion ART briefly. Fusion ART is a self-organizing neural network that is an extended model of ART (Mermillod et al. 2013).

3.1 Fusion ART

The following procedures are involved in a Fusion ART.

3.1.1 Complement coding

Each field F_1^k receives an input vector $\mathbf{I}^k = (I_1^k, I_2^k, \ldots, I_n^k)$ where $I_i^k \in [0, 1]$, $i = 1, 2, \ldots, n$, denotes the i-th input or attribute to channel k and $k = 1, 2, \ldots, l$ is the number of input attribute channels. Each of the input vector $\mathbf{I}^k$ is converted into an activity vector $\mathbf{x}^k$ by the process of complement coding in which the input vector is concatenated with its complement, $\bar{\mathbf{I}}^k = (1 - \mathbf{I}^k)$.

3.1.2 Parameters

Each field's dynamics are determined by various parameters. These include choice parameters α^k, learning rate parameters β^k, contribution parameters γ^k, and vigilance parameters ρ^k.

3.1.3 Code activation

F_2 has one channel that is represented by an activity vector $\mathbf{y} = (y_1, y_2, \ldots, y_d)$ where d is the number of nodes in F_2. The following choice function activates a node j in F_2:

$$T_j = \sum_{k=1}^{l} \gamma^k \frac{\left|\mathbf{x}^k \wedge \mathbf{w}_j^k\right|}{\alpha^k + \left|\mathbf{w}_j^k\right|} \tag{1}$$

where x^k is the activity vector of F_1^k receiving the input $\mathbf{I}^k$ (including the complement), $\mathbf{w}_j^k$ denotes the weight vector associated with the j-th node in F_2 for learning the input pattern in F_1^k, α_k is the choice parameter, and $\gamma^k \in [0, 1]$ is the contribution parameter. Also, $k = 1, 2, \ldots, l$ is the number of input channels, $\wedge$ represents a fuzzy AND operator where $\wedge$: $\mathbf{a} \wedge \mathbf{b} = (min(a_1, b_1), min(a_2, b_2), \ldots, min(a_D, b_D))$ for the D-dimensional vectors, a and b, and norm operator is defined by $|\mathbf{a}| = \sum_{i=1}^{D} |a_i|$.

3.1.4 Code competition

The node with the highest activation value in F_2 is selected as the winner node by the process of code competition where the winner node is indexed at J as

$$T_J = \max\{T_j : \text{for all } F_2 \text{ node } j\}. \tag{2}$$

Making use of the winner-take-all strategy, the output of the winner node is set to 1 and all the other outputs are set to 0.

3.1.5 Template matching

This process is used to check the similarity between the activity vector $\mathbf{x}^k$ and the weight vector $\mathbf{w}_J^k$, which is associated with the selected node in F_2. This similarity is defined by the value given by the following match function:

$$m_J^k = \frac{\left|\mathbf{x}^k \wedge \mathbf{w}_j^k\right|}{\left|\mathbf{x}^k\right|} \tag{3}$$

and the vigilance criterion is as follows:

$$m_J^k \geq \rho^k. \tag{4}$$

In order for resonance to occur (4) should be true. In other words, the match value of the selected node J should be greater than the vigilance parameter ρ^k. Vigilance parameter ρ^k sets a threshold for the template matching step. For OFM, we have modified (4) to

$$m_J^k \geq \rho^k \gamma^k \tag{5}$$

like in Leconte et al. (2015) where $\gamma^k \in [0, 1]$. This is done to control the vigilance parameter for each channel based on the contribution factor associated with that channel. It could be useful if one wants to either give relative significance to certain attributes at the input or ignore some of them. Assigning γ^k equals to zero specifies that no importance is currently being given to the attribute coming from channel k in the match process. If (4) and (5) are not true for episodic memory and OFM, respectively, a reset occurs setting the value of T_J to 0. Until resonance is achieved, a new index j is chosen by (2). In the case when no node meets vigilance criterion, a new category node is created in F_2.

3.1.6 Template learning

After resonance occurs in F_2, the weight vectors are modified for each channel using the following learning rule:

$$\mathbf{w}_J^{k(new)} = (1 - \beta^k)\mathbf{w}_J^{k(old)} + \beta^k(\mathbf{x}^k \wedge \mathbf{w}_J^{k(old)}). \tag{6}$$

3.1.7 Readout

Once a node J is chosen in F_2, it can readout its weight vectors by a top-down process to an input field F_1^k such that $\mathbf{x}^{k(new)} = \mathbf{w}_J^k$.

Notation In the remainder of the paper, the leading superscript o is used to identify the notation for the OFM to differentiate it from the notation of the episodic memory and consolidated memory.

Figure 2 shows the architecture of OFM made by hierarchically joining two Fusion ARTs. An object has the general representation as *Object*: $\left\{{}^o\mathbf{I}^1, {}^o\mathbf{I}^2, \ldots, {}^o\mathbf{I}^q\right\}$, where ${}^o\mathbf{I}^k$ represents an attribute vector to channel k and q is the number of attribute channels for ${}^oF_1$. Each attribute channel represents information that is required to encode an object. For example, *ObjectLabel*, *Color*, *Characteristics*, *Location*, etc. can be used to encode an object where *ObjectLabel* refers to the label given to the object for identification and learning.

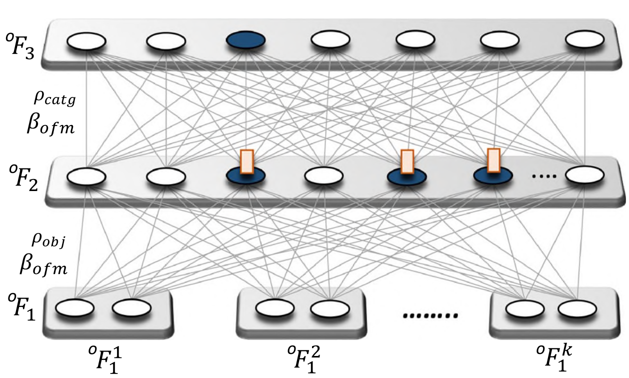

Fig. 2 OFM architecture

Following the dynamics of Fusion ART, an activity vector of the attribute layer ${}^oF_1$ undergoes code activation, code competition, template matching, and template learning to learn every u-th object o_u in the object layer ${}^oF_2$. Hence, by updating the weights in the connections between ${}^oF_1$ and ${}^oF_2$, an incoming object is said to be learned using the learning rate β_{ofm}. The same dynamics are used to learn a pattern of activations in layer ${}^oF_2$ as the v-th object category O_v in ${}^oF_3$. The most recent activated node in layer ${}^oF_2$ gets the value of 1 and the previously selected nodes also keep the value of 1 without any decay. This ensures that the object categories learned in ${}^oF_3$ are independent of any temporal sequence. Note that a the term category is used to define a set of objects while the term node is used to refer to a point in the network that could either be an object, a category, an episode, etc. Once the OFM is constructed, an attribute-based semantic relation (*ASR*) value V_A^{att} can be calculated by

$$V_A^{att} = \frac{\sum_{k=1}^{q} \phi^k \frac{|\mathbf{w}_1^k \wedge \mathbf{w}_2^k \ldots \wedge \mathbf{w}_c^k|}{\alpha^k + |\mathbf{w}_1^k \vee \mathbf{w}_2^k \ldots \vee \mathbf{w}_c^k|}}{\sum_{k=1}^{q} \phi^k} \tag{7}$$

where $V_A^{att} \in [0, 1]$ is the attribute semantic relation value between any number of categories defined by a subset $A \subseteq \tilde{U} = \{1, 2, \ldots, c\}$ such that the cardinality of A is at least 1 and c is the maximum number of categories. $\mathbf{w}_O^k$ is the weight vector for an object from category O between ${}^oF_2$ and ${}^oF_1$ where $O = 1, 2, \ldots, c$; $\vee$ represents a fuzzy OR operator with $\vee$: $\mathbf{a} \vee \mathbf{b} = (max(a_1, b_1), max(a_2, b_2), \ldots, max(a_D, b_D))$ for the D-dimensional vectors, $\mathbf{a}$ and $\mathbf{b}$. Finally, $\phi^k \in [0, 1]$ is the relevance parameter. The value of the relevance parameter for each of the channels k describes how relevant that channel is for calculating the *ASR* value. The *ASR* value defines associations between any number of categories, the strength of which depends on the number of attributes shared by the particular categories. This value of a category with itself is maximum. Using such relations between any number of categories, we can define tensors of rank $c' \in [1, c]$ defining the scalar (self), vector (one category with each of the other c categories), pair-wise (all c categories with each of the other c categories), triple-wise, quadruple-wise,..., etc. *ASR* values. The general attribute semantic relation tensor (T_{SRT}^{att}) would then be

$$T_{SRT}^{att} = (V_{\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_{c'}}^{att}) \tag{8}$$

Algorithm 1 pMM-ART: OFM Learning

1: **BEGIN**
2: **FOR** every subsequent object o_u in object category O_v
3: Based on input ${}^oI_k$ in ${}^oF_1$, select a resonant node U in ${}^oF_2$
4: Let node activation y_U be 1 or any predefined maximum value
5: After a subsequent presentation of O_v, given an activation vector y formed in ${}^oF_2$
6: Select a resonant node V in ${}^oF_3$ on the basis of the activation vector y
7: **if** O_v is a novel object category **then**
8: learn its associated weight vector $w_V^{(new)} = y$
9: **end if**
10: Construct T_{SRT}^{att} using (9)
11: **END**

where λ is used for indexing purpose. When $c' = 2$, it reduces to a rank-2 tensor which is essentially a $c \times c$ matrix as shown below. It defines the relationship between each of the O-th category with itself and the remaining $c - 1$ categories.

$$T_{SRT}^{att}\big|_{c'=2} = \begin{pmatrix} V^{att}_{\lambda_1=1,\lambda_2=1} & V^{att}_{\lambda_1=1,\lambda_2=2} & \cdots & V^{att}_{\lambda_1=1,\lambda_2=c} \\ V^{att}_{\lambda_1=2,\lambda_2=1} & V^{att}_{\lambda_1=2,\lambda_2=2} & \cdots & V^{att}_{\lambda_1=2,\lambda_2=c} \\ \vdots & \vdots & \ddots & \vdots \\ V^{att}_{\lambda_1=c,\lambda_2=1} & V^{att}_{\lambda_1=c,\lambda_2=2} & \cdots & V^{att}_{\lambda_1=c,\lambda_2=c} \end{pmatrix}. \tag{9}$$

We will later see in Sect. 7 that the inference model makes use of the attribute semantic relation tensor when there is a need to search for the category with which the currently activated category shares the maximum *ASR* value. It is also used to search for multiple categories with which the activated category shares high *ASR* values. The learning process of objects and object categories is highlighted in Algorithm 1.

An object category can be retrieved by a top-down readout procedure using a retrieval cue. The retrieval cue activates an object node in ${}^oF_2$, and it is selected as the incoming object if the match is high enough to pass the vigilance criterion ρ^{obj}. The activated objects in ${}^oF_2$ are then recognized as the objects in the retrieval cue. A similar process then takes place between ${}^oF_2$ and ${}^oF_3$ to recognize the object category. Once the object category is recognized, it is selected and the weights are readout by a top-down process: first from ${}^oF_3$ to ${}^oF_2$ and then from ${}^oF_2$ to ${}^oF_1$. In this manner, the entire list of objects in the chosen object category is retrieved. In order to facilitate a flexible retrieval of object categories, a low vigilance threshold ρ^{catg} is used between layers ${}^oF_2$ and ${}^oF_3$. However, to reduce erroneous retrievals of object categories, a high vigilance criterion is used between layers ${}^oF_1$ and ${}^oF_2$ to set a strict matching criterion for the individual objects.

4 Encoding and learning of episodes in pMM-ART

The encoding and learning of episodes in pMM-ART is the same as that for pDM-ART in Nasir et al. (2018). We present the relevant content from Nasir et al. (2018) in condensed form in this section which is sufficient for the purpose of this paper to understand the integration between the episodic memory and OFM. An overall architecture of pMM-ART is shown in Fig. 3 in which F_1, F_2, and F_3^{epi} represent the episodic memory while F_3^{sem} represents the consolidated experiences/semantic concepts as defined in Nasir et al. (2018).

While the basic encoding, learning, and retrieval procedure for the episodes in pDM-ART is the same as that for object categories described in the previous section, there are certain differences that give episodic memory (1) its spatio-temporal characteristic [adapted from Wang et al. (2012a)] and (2) various learning rates based on a user-preference known as Importance factor I [introduced in Nasir et al. (2018)]. The higher the importance associated with an event, the stronger the encoding is compared with other events at the time of encoding (Nasir et al. 2018). Note that the number of input channels for F_1 and attribute channels for ${}^oF_1$ are independent of each other. We use l and q number of input and attribute channels for F_1 and ${}^oF_1$, respectively, for the purpose of clarity.

An event including an action input $\mathbf{I^1}$ and object input $\mathbf{I^2}$ and an importance I is represented as *Event*: {Action($\mathbf{I^1}$), Object($\mathbf{I^2}$)| Importance I}. Events are learned as weights between the layers F_1 and F_2 using various learning rates represented by β_{e_j} where β_{e_j} is the learning rate for j-th event and is given by:

$$\beta_{e_j} = \beta_{min} + (1 - \beta_{min})(I_{e_j} - 0.5). \tag{10}$$

Here $I_{e_j} \in [0, 1]$ is the importance of the event e_j defined by the user at the input layer. and $\beta_{min} \in [0.5, 1]$ is the initial setting of the minimum learning rate of the memory model. Just as a pattern of activations in ${}^oF_2$ is used to represent an object category in ${}^oF_3$, the activation patterns in F_2 represent an episode in F_3. These episodes are learned as weights between F_2 and F_3 based on β_{E_r} defined in a similar manner as (9). β_{E_r} is controlled by $I_{E_r} \in [0, 1]$, that is, the importance factor for the r-th episode. I_{E_r} is given by

$$I_{E_r} = \frac{\sum_{j=1}^{p} I_{e_j}}{p} \tag{11}$$

where p is the total number of events in the r-th episode and I_{e_j} is the importance of the j-th event in the r-th episode.

In contrast to the activation values being either 1 or 0 in ${}^oF_2$, in episodic memory a decaying pattern of activations

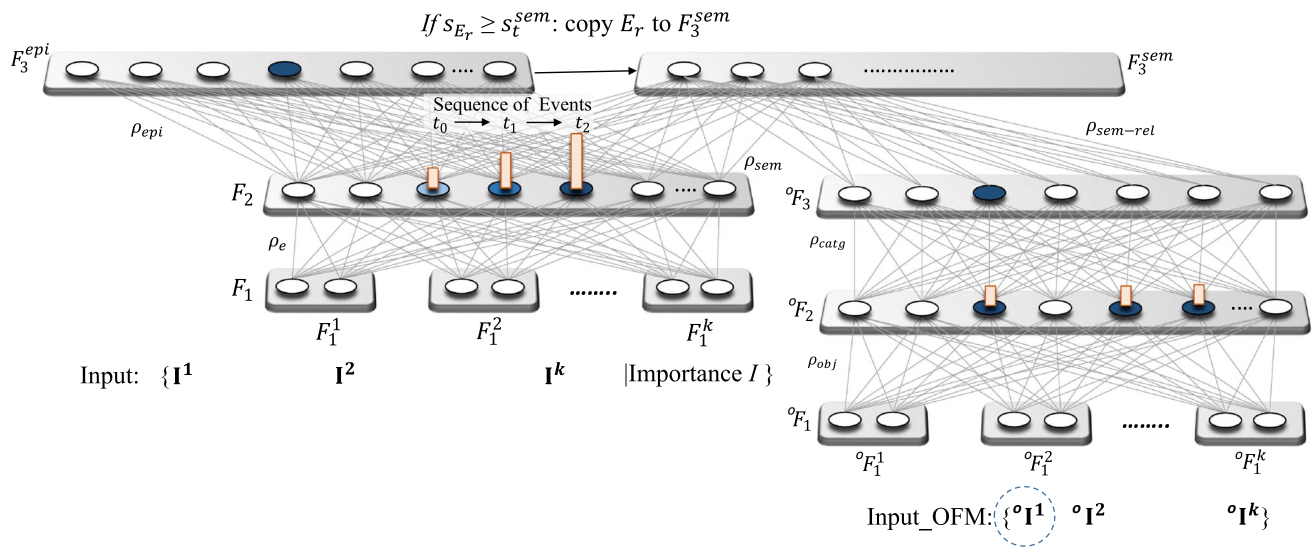

Fig. 3 pMM-ART architecture

represents the sequence of events in the episode (Wang et al. 2012a). The most recently activated event node is assigned a value of 1 while the activation values of the event nodes that were selected previously are decayed over time by a decaying factor given by $\tau \in (0, 1)$ such that $y_j^{new} = y_j^{old}(1-\tau)$ where $\mathbf{y}$ is the activity vector of F_2. Hence, an episode is learned as a decaying pattern of activations representing the sequence of events in time.

In order to read out the events in correct sequence from F_2 to F_1 during the retrieval procedure, a vector is used that first complements the values in F_2 such that $\bar{y}_j = 1 - y_j$. Making use of this complement vector, the weights of the event node associated with the highest value are read out first from F_2 to F_1 to retrieve the sequence of the events in the correct order as they were learned.

5 Retrieval, memory consolidation and integration

This section describes how in the presence of the OFM, the retrieval of episodic memory from F_3^{epi} and the following memory consolidation procedure described in pDM-ART (Nasir et al. 2018) can be utilized to form top-down weights in pMM-ART. These weights are formed (1) between the consolidated episodes/semantic concepts and the object categories in the OFM and (2) between the object categories based on the concepts they share. In effect, this leads to the integration of episodic memory and semantic memory.

A cue for retrieving an episode with an action input $\mathbf{I^1}$ and object input $\mathbf{I^2}$ is represented as *Retrieval cue*: $\{$Action$(\mathbf{I^1})$, Object$(\mathbf{I^2})\}$. The input cues for an episode are first received by the working memory that acts as a buffer until all cues for a single episode are received. It passes these cues onto the inference module to infer the type of objects that are in the cue. For this purpose, the inference module queries information through working memory about the objects in episodic memory and those that are in the OFM. In our implementation, it is assumed that the OFM has also learned some objects that are not a part of the episodic memory. We refer to these kind of objects as objects without context. Similarly, a category in OFM with all such objects would be referred to as a category without context.

5.1 Retrieval via F_3^{epi} and F_3^{sem}

If all the objects in the retrieval cue are associated with a context then the inference module directs the cues to episodic memory to retrieve an episode using either of the two routes to F_3^{epi} and F_3^{sem} in the same way as in pDM-ART. The two routes, from F_2 to episodic memory F_3^{epi} and F_2 to semantic memory F_3^{sem}, have different vigilance values, ρ_{epi} and ρ_{sem}, respectively. ρ_{sem} is always lower than ρ_{epi} to facilitate easier retrieval. Before the formation of F_3^{sem}, only F_3^{epi} is used (Nasir et al. 2018).

In addition to this, in pMM-ART, the information about the objects in the retrieval cue is also sent to the attribute layer $^oF_1$ to activate the relevant object categories. In the current implementation, the retrieval cues include information about objects and actions but not the object attributes. Therefore, we set the contribution factor, γ^k, equal to zero for all attribute channels except *label* channel $^oF_1^1$ during the retrieval process for pMM-ART. Alternatively, attributes can also be used at the input layer.

At the time of encoding of events and episodes, pDM-ART (Nasir et al. 2018) assigns a memory strength value to each event and episode according to their importance factor I. This ensures that the more important episodes are encoded strongly compared to less significant ones. Every time an event or episode is reactivated, the memory strength value is strengthened proportional to a reinforcement rate r_s and the memory strengths for other events and episodes decay by a decay factor δ_s.

If the memory strength of an event or episode falls below a certain threshold, it is forgotten. That is, it is removed from the episodic memory. On the other hand, if the memory strength of an episode exceeds the semantic-like memory threshold value $s_t^{sem} \in [0, 1]$, the episode is moved to the semantic-like memory F_3^{sem}. This episode is then called a consolidated episode/semantic concept and has the memory strength value at which it got consolidated. Each episode consolidates at a rate directly proportional to (1) the importance I assigned to the episode at the time of encoding and (2) the frequency of retrieval of that episode.

For the purpose of facilitating integration between pDM-ART and OFM, we introduce top-down weights that are formed between the consolidated episode and the currently activated set of object categories in ${}^{o}F_3$. The weight values are equal to the memory strength value of the consolidated episode. For the resonant node R in F_3^{epi} that gets consolidated and copied in F_3^{sem}, the values of the weights in the weight vector $\mathbf{w}_R^{(catg)}$ associated with the categories in ${}^{o}F_3$ would be:

$$\begin{cases} s_{E_R}(t), & \forall \text{ currently activated } O \quad \text{(12a)} \\ 0, & \forall \text{ currently non-activated } O. \quad \text{(12b)} \end{cases}$$

In the case when an object category has weighted connections with more than one consolidated episode, the weight values will be the highest for the one with the highest memory strength value $s_{E_R}(t)$. The object categories that share concepts form an association with each other which we term as a concept-based semantic relation (*CSR*). This relation V_A^{con} between any number of categories defined by a subset $A \subseteq \tilde{U} = \{1, 2, \ldots, c\}$, is determined as follows:

$$V_A^{con} = \frac{\textit{No. of concepts shared between A categories}}{\textit{No. of categories sharing the concepts}} \tag{13}$$

This value is updated whenever a new concept is shared between the same set of object categories. The value can range between $[0, max]$ where max can be any real valued number, and, just like V_A^{att}, V_A^{con} can be used to define associations between any number of categories from one to maximum c. For example, $V_{\lambda_1=1,\lambda_2=3}^{con} = 1.5$ means that categories 1 and 3 share three concepts. A cardinality of one for A defines the *CSR* value of a category with itself, which is simply equal to the number of concepts with which it is associated. Similarly, using relationships between any number of categories, we can define a tensor of rank $c' \in [1, c]$ (T_{SRT}^{con}) (known as Concept Semantic Relation Tensor) similar to (9). As we indicate in Sect. 7, this tensor is used by the inference module to search for categories that share the highest *CSR* value with the currently activated category/categories.

5.2 Retrieval via F_3^{sem} and OFM via inference

In the case when the inference module receives retrieval cues with an object that is not associated with any learned episode, it directs the cues to OFM only. Each object in the retrieval cues is used to activate the relevant categories in the ${}^{o}F_3$ layer. In order to make a prediction for a plan that is most relevant to the incoming retrieval cues, the inference model makes use of the weighted connections between (1) object categories and semantic concepts/consolidated episodes (V_A^{con}) and (2) object categories (V_A^{att}).

First, an activation value for each consolidated episode in F_3^{sem} at the incoming pattern of object categories is calculated (more on this in Sect. 7). It is given by a sum of weights between the consolidated episode and each of the activated object categories. The activation values undergo the following vigilance criterion:

$$\rho_{sem-rel} = \frac{\zeta}{s_t^{sem}} \tag{14}$$

where $\zeta \in (0, 1]$ is a constant of proportionality. The lower the value of s_t^{sem}, the stricter the vigilance criterion is. The inverse relation in (14) between $\rho_{sem-rel}$ and s_t^{sem} is intuitive. The value of $\rho_{sem-rel}$ should be higher when the semantic-like memory threshold has a low value and vice versa. This is because more episodic memories will get consolidated quickly if s_t^{sem} is lower. Hence, a stricter criterion must be applied between ${}^{o}F_3$ and F_3^{sem} opposed to when the consolidation itself undergoes a strict s_t^{sem} criterion. All consolidated episodes with activation values fulfilling the vigilance criterion $\rho_{sem-rel}$ are retrieved in the order of priority. The consolidated episode with the highest activation value has the highest priority. The weights are read out from F_3^{sem} and F_2.

In the case when the vigilance criterion $\rho_{sem-rel}$ is not fulfilled for each consolidated episode, then T_{SRT}^{con} helps to predict a sequence of events closest to the retrieval cue. Apart from the categories that are activated due to the incoming retrieval cue, a few more categories are additionally activated. These are the categories that respectively have the highest V_A^{con} values with each of the already activated categories.

The categories having the highest V_A^{con} values with each of the activated categories (due to the incoming retrieval cue) are activated. Together these categories are used to meet the vigilance criterion and retrieve a consolidated episode.

The retrieved semantic concept is the closest plan to the task at hand; however, it contains information about different, though semantically related, objects that were originally learned in the episodic memory. The inference module makes appropriate replacements based on the similarity between the objects in the retrieved sequence of events and those in the retrieval cue. Objects from the same categories can replace each other in a retrieved sequence of events. For example, after having learned *Move Apple from Counter to Fridge*, pMM-ART is expected to be able to predict the sequence of events for *Move Orange from Table to Cupboard* since *apple, orange*; *table, counter*; and *cupboard, fridge* are semantically related to each other in our representation of the OFM (more on this in 7). Another possible case of object replacement is when the two objects belong to different categories but the value of V_A^{att} between the two is high enough to meet a vigilance criterion $\rho_{att} \in [0, 1]$. For example, *coffee* and *pepsi* may be able to replace each other even though they belong to different categories of hot and cold drinks in our simulation test bed. This allows for planning in cases when one of the objects in the retrieval cue belongs to a category that has no context. T_{SRT}^{att} can be used to identify if enough attributes are shared between this category and the category in the retrieved sequence of events. If the criterion ρ_{att} is met, the plan would be considered feasible for the incoming category without context.

The procedure for retrieval, memory consolidation, and formation of weights (V_A^{att}, V_A^{con}) is written in the form of psuedocode in Algorithm 2 for easier understanding.

Algorithm 2 pMM-ART- Retrieval, Consolidation and formation of 1) T_{SRT}^{con} 2) T_{SRT}^{att}

1: **BEGIN**
2: **FOR** the incoming retrieval cues of one episode/task
3: **if** all objects are associated with context **then**
4: Send to episodic memory to retrieve from $F_3^{epi} \cup F_3^{sem}$
5: Also, activate relevant object categories in ${}^oF_3$
6: Select a resonant node R in $F_3^{epi} \cup F_3^{sem}$
7: **if** R is found in F_3^{epi} **then**
8: Increase $s_{E_R}(t)$ for R by
9: $s_{E_R}(t) = s_{E_R}(t-1) + (1 - s_{E_R}(t-1))r_s$
10: **end if**
11: **for** every other node **do**
12: Decrease $s_{E_R}(t)$ by
13: $s_{E_R}(t) = s_{E_R}(t-1)(1-\delta_s)$
14: **end for**
15: **if** s_{E_R} for R is $\geq s_t^{sem}$ and R is not in F_3^{sem} **then**
16: Copy R to semantic memory component F_3^{sem}
17: Learn the associated weight vector $\mathbf{w}_R^{(sem)} = \mathbf{w}_R^{(epi)}$
18: Form weights between R in F_3^{sem} and currently active O_v in ${}^oF_3$
19: Update relevant values in T_{SRT}^{con}
20: **end if**
21: Readout weights from F_3^{epi} and F_2 or F_3^{sem} and F_2
22: **end if**
23: **if** one or more objects are not associated with any context **then**
24: Send to OFM to retrieve from F_3^{sem} and ${}^oF_3$ via inference
25: Activate relevant object categories in ${}^oF_3$
26: Sum the weight values between each consolidated episode in F_3^{sem} and currently active O in ${}^oF_3$ to get the activation values for each concept
27: **if** one or more activation values $\geq \rho_{sem-rel}$ **then**
28: Retrieve the relevant concepts in order of priority
29: **if** at least one O has no context **then**
30: Use T_{SRT}^{att} to validate ρ_{att} criterion if possible for O without context
31: **end if**
32: **end if**
33: **if** all activation values $< \rho_{sem-rel}$ **then**
34: Use T_{SRT}^{con} to activate category/categories closest to the already active categories
35: Repeat steps 26–29 again
36: **end if**
37: Reorganize the retrieved sequence of events using appropriate object replacements
38: **end if**
39: Exit Loop
40: **END**

6 Complexity analysis

We analyze the space complexity and time complexity of pMM-ART for encoding and retrieving events, episodes, objects, and object categories. Let us consider the task of encoding E episodes, e unique events, O object categories, and o unique objects. The basis for defining the complexity is the same for OFM, PDM-ART, and EM-ART (Tan et al. 2007), since they are constructed using Fusion ART. We suppose that for each event and each object there are fixed set of attributes a and ${}^oa$. In one category, there can be a maximum of G objects and on average g objects. Similarly, there can be a maximum of M events and an average of m events in an episode. Lastly, in F_3^{sem}, we can have a maximum of E episodes and a minimum of 0 episodes. Table 1 shows the space and time complexity for OFM, pDM-ART, and EM-ART, since we used it as a benchmark for pDM-ART in Nasir et al. (2018), and pMM-ART.

6.1 Space complexity

OFM would require a total of o nodes to encode o objects in the ${}^oF_2$ layer and a total of O nodes to encode O object categories in the ${}^oF_3$ layer. Since an object o is stored in the $2({}^oa)$ weighted connections to the ${}^oF_1$ layer, there are a total of $2o({}^oa)$ connections between ${}^oF_1$ and ${}^oF_2$ layers. Similarly, as each O node is connected to all the o nodes, there are a total of $2Oo$ between layers ${}^oF_2$ and ${}^oF_3$. In the same way, we get a total of $2ea$ and $2Ee$ weighted connections between F_1 and F_2 layers and F_2 and F_3 layers, respectively. Also,

Table 1 Comparison of space and time complexity

	OFM	pDM-ART	EM-ART	pMM-ART
Space complexity (nodes)	$O(o + O)$	$O(e + E)$	$O(e + E)$	$O(e + E + o + O)$
Space complexity (weights)	$O(o(^oa) + Oo)$	$O(ea + Ee)$	$O(ea + Ee)$	$O(ea + Ee + o(^oa) + Oo + EO)$
Time complexity (Encoding)	$O(go(^oa) + Oo^2)$	$O(mea + Ee^2)$	$O(mea + Ee^2)$	$O(go(^oa) + Oo^2 + mea + Ee^2 + EO + (c-1)!)$
Time complexity (Retrieving)	$O(go(^oa) + Oo^2)$	$O(mea + Ee^2)$	$O(mea + Ee^2)$	$O(go(^oa) + Oo^2 + mea + Ee^2 + EO + (c-1)!)$

in F_3^{sem} there can be a maximum of E nodes if all episodes are consolidated or a minimum of 0 if none are consolidated. Lastly, the maximum number of weights between F_3^{sem} and $^oF_3$ can be EO and a minimum of 0. Hence, the minimum number of nodes required in pMM-ART is $e+E+o+O$ and a maximum of $e + 2E + o + O$ nodes. In the same manner, a minimum of $2(ea + Ee + o(^oa) + Oo)$ and a maximum of $2(ea + 2Ee + o(^oa) + Oo) + EO$ connections are required in pMM-ART. Although it seems that the addition of OFM increases the space complexity, in effect, if there was to be no use of OFM and instead the memory model was to learn all kinds of similar interactions through episodic memory, the number of nodes would be much higher. Using V_A^{con}, and V_A^{att} reduce the number of events, episodes and weights required to "know" a particular amount of events and episodes/tasks.

6.2 Time complexity

In OFM, for the resonance search operation between $^oF_1$ and $^oF_2$, a total of $o(^oa)$ comparisons are required. For an average of g objects in one object category, the processing steps required to produce activations in $^oF_2$ are $go(^oa)$. To compare the activation pattern in $^oF_2$ with O number of object categories in $^oF_3$, it will require Oo^2 amount of processing time. This makes the time associated with encoding an object category equal to $go(^oa) + Oo^2$. In a similar manner, we can see that if there are no nodes in F_3^{sem}, the time required to encode an episode is $mea + Ee^2$ and $mea + 2Ee^2$ in the case when there are E number of nodes in F_3^{sem} (Nasir et al. 2018). Also, the time required to process connections between E number of concepts in F_3^{sem} and O number of object categories in $^oF3$ is EO. To calculate T_{SRT}^{con} and T_{SRT}^{att}, a total of $2(c-1)!$ calculations are required. This makes the time complexity of pMM-ART equal to $go(^oa) + Oo^2 + mea + Ee^2 + EO + (c-1)!$ as shown in Table 1.

7 Functioning principle and discussion

In this paper, we focus on exploiting the semantic hierarchy of objects for enhancing the behavior of an autonomous agent in three ways. For example, if it learns to plan for "*Move apples from counter to fridge*", it should also be able to plan for "*Move oranges from table to shelf*" if we assume *apples, orange*, *counter, table*, and *fridge, shelf* to be in semantically similar categories. Also, if pMM-ART receives cues for "*Move oranges from counter to Not-Kitchen-Cabinet*", it should be able to deduce: (1) it learned moving objects of the type *orange* (belonging to the category *fruits*) to objects belonging to category *kitchenstorage* and (2) *Not-Kitchen-Cabinet* does not belong to the category *kitchenstorage*. Hence, it will retrieve the plan for the task by correcting the possible furniture type needed to store *oranges*.

This section demonstrates the functioning principle of the preliminary version of our model in a simplistic test bed in a MATLAB environment to examine the potential of a system that looks to exploit relationships between episodic memory and semantically related categories of objects. The test bed consists of plans for five tasks/episodes, as shown in Table 2, and 10 categories consisting of 29 objects. We examined the model with various kinds of cues to observe the number of different tasks/plans that it could execute using the knowledge of 5 tasks and 10 object categories. The first step was learning of episodes and object categories. Two inputs were used to learn the events: a total of 6 actions {*Grasp, Move, Putdown, Open, Close, Wash*} and 9 objects {*Apple, Fridge, Counter, Cola, User, CircularToy, NotKitchenTable, NotKitchenCupboard*}. The tasks were learned using the episodic memory module and OFM was used to learn a set of 10 object categories {*Fruit* = *Apple, Banana, Orange, ColdDrink* = *Cola, Pepsi, Cider; HotDrink* = *Milk, Tea, Coffee, KitchenStorage* = *Fridge, Cupboard, Shelf, KitchenSurface* = *Counter, Table, Slab, HumanSubject* = *User, Friend, StorageFurniture* = *NotKitchenCupboard, NotKitchenShelf, ToyWithoutEdges* = *CircularToy, OvalToy, SphericalToy, SharpEdgedToy* = *SquareToy, RectangularToy, PentagonToy, Surface* = *NotKitchenCounter, NotKitchenTable, NotKitchenSlab*}. At the attribute layer $^oF_1$, we used 4 channels to define 29 objects. The first channel was the *label* channel which includes labels for each object like *Apple, Shelf*, etc. The second channel was for defining 9 colors {*Red, Green, Blue, Yellow, Orange, Black, White, Pink, Brown*}. The third channel defined 8 characteristics {*Sustenance, Eatable, Drinkable, CanStore, Sharp, Rounded, Playable, Flat*}. Finally, the last channel defined

Table 2 A detailed list of the scenarios along with their respective sequence of events

Scenario	Sequence of events
Move apples from counter to fridge	Move to the counter
	Pick an apple
	Move with the apple to the fridge
	Open the fridge
	Putdown the apple
	Close the fridge
Bring Cola for a user	Move to the fridge
	Open the fridge
	Pick a Cola
	Close the fridge
	Move to the user
Move apples from counter to fridge after washing	Move to the counter
	Pick an apple
	Wash the apple
	Move with the apple to the fridge
	Open the fridge
	Putdown the apple
	Close the fridge
Arrange circular toys	Move towards a circular toy
	Grasp a circular toy
	Move with the circular toy to a table that is NOT in kitchen
	Put the toy on the table
Arrange rectangular toys	Move towards a rectangular toy
	Grasp a rectangular toy
	Move with the rectangular toy to a cupboard that is NOT in kitchen
	Put the toy in the cupboard

locations of the objects $\{Kitchen, NotKitchen\}$. The tasks were designed in a way to test the aforementioned abilities of pMM-ART in a typical domestic environment. Some of the most common tasks in such an environment may be to arrange fruit with or without washing them, to provide a beverage to the user, and to arrange random toys in the house differentiating safe toys (with circular edges) from less safe toys (with pointed corners). The test bed is designed to analyze the functioning principle and to understand the abilities and limitations of the currently defined pMM-ART.

For setting the importance factor I at the time of the encoding of events, a *feedbackfunction()* is used that mapped user feedback to a pre-defined function where the user feedback can be recorded in various ways including verbal or facial expressions (Nasir et al. 2018). Once the system learned the episodes/tasks and the object categories, it is tested with various kinds of cues in a number of cases. We set a high importance factor of 1 with all the events except the event of *washing apples*. It is given a value of 0.5 to signify that the user does not prefer washing the apples. Various retrieval cues are used. Case one defines a situation in which the retrieval cues include a sequence of events for a task with objects that the system was taught planning with initially. In other words, all objects have a context meaning that are known to episodic memory. The second case defines the situation in which one or more objects in the cues are unknown to the episodic memory. The last case is when one or more objects or object categories and an event/sequence of events is unknown to episodic memory.

Parameters for pMM-ART: Parameters for pMM-ART were initialized as follows:

- $\rho_e = 0.98$, $\rho_{epi} = 0.98$, $\rho_{sem} = 0.65$, $\beta_{min} = \gamma_{min} = s_{min} = 0.5$, $\delta_s = 0.0001$, $r_s = 0.5$ and $s_t^{sem} = 0.75$
- $\rho_{obj} = 0.95$, $\rho_{catg} = 0.87$, $\beta_{ofm} = 0.8$ (for all channels from layer ${}^oF_1$ to ${}^oF_2$, and from ${}^oF_2$ to ${}^oF_3$), $\gamma = 1$ (at learning for all channels and layers), $\gamma = 0$ (at retrieval for all channels in ${}^oF_1$ except for ${}^oF_1^1$, $\rho_{sem-rel} =$

Table 3 Summary of results for a scenario of 5 learned tasks

Learning		
Number of events learned		19
Number of episodes/task learned		5
Number of objects learned		29
Number of objects categories learned		10
	Retrieval	
	With OFM	Without OFM
Number of events retrieved	83	19
Number of tasks it can plan for	99	5
Number of times it used T^{con}_{SRT} and succeeded	11/11	
Number of times it used T^{att}_{SRT} and succeeded	18/36	
Number of times it was able to identify erroneous object category	9/9	
Number of times it showed a lack of plan	48	
Successful retrieval including all cases	$5/5 + 107/107 + 27/93 = 139/205$	

$1/s^{sem}_t = 1.333$, $\rho_{att} = 0.75$, and $\phi^k = 0$ for k=0,1 and $\phi^k = 1$ for k=2,3.

Parameters were chosen by a hit-and-trial method in a way that worked best in the current environment. It was found that OFM was very sensitive to changes in the values for ρ_{catg}. According to our observation, intermediate values (between 0.8 and 0.9) were more suitable for forming discrete clusters of objects when there were no categories with a single object. Otherwise, higher values (above 0.95) of ρ_{catg} produced best results during training. In the latter case, the value of ρ_{catg} can be tuned during testing to increase flexibility. The summary of the results in this section is shown in Table 3.

7.1 Case I: Cues with objects known to episodic memory

In this case, we have different kinds of cues that can be used to evaluate the performance of the episodic memory. Partial cues from the beginning, partial cues from the middle, partial cues from the end, noisy cues in terms of event representation, and noisy cues in terms of event sequence were used. For each kind of cue, the test was carried out with (1) multiple trials with each trial having the same set of cues and (2) three cases of importance parameter values to evaluate the effect of the importance parameter on consolidation. For Case I, as OFM is not needed, pMM-ART in effect reduces to pDM-ART (Nasir et al. 2018) in its performance except that at consolidation weighted connections are formed with ${}^oF_3$. For the sake of space constraints and keeping the paper focused on the advantages of integrating an OFM with episodic memory, these simulations have not been included in more detail. The interested reader is requested to refer to Nasir et al. (2018) for a better understanding. After the consolidation of all the episodes and hence the formation of (1) T^{con}_{SRT} and (2) T^{att}_{SRT}, the partial structure of pMM-ART will look as shown in Fig. 4. We will get to the Extended Concept shown in Fig. 4 in more detail in 7.2.

7.2 Case II: Cues with one or more objects unknown to episodic memory

In the second case, objects unseen by the episodic memory were used in the retrieval cues. This means that these objects were not learned by the episodic memory in any episode. Rather, they are only known to the OFM as a part of a category. Two types of cues were used: (1) complete cues and (2) partial cues.

7.2.1 Retrieval with complete cues

A total of 81 cues were used with 76 of them being complete cues with objects unknown to episodic memory while the remaining five cues were cues for the five learned tasks. These first five cues were needed for consolidation, and since we set a high importance factor of 1 with each event, consolidation of a particular episode was achieved only after one successful retrieval through F^{epi}_3. The effect of I on the rate

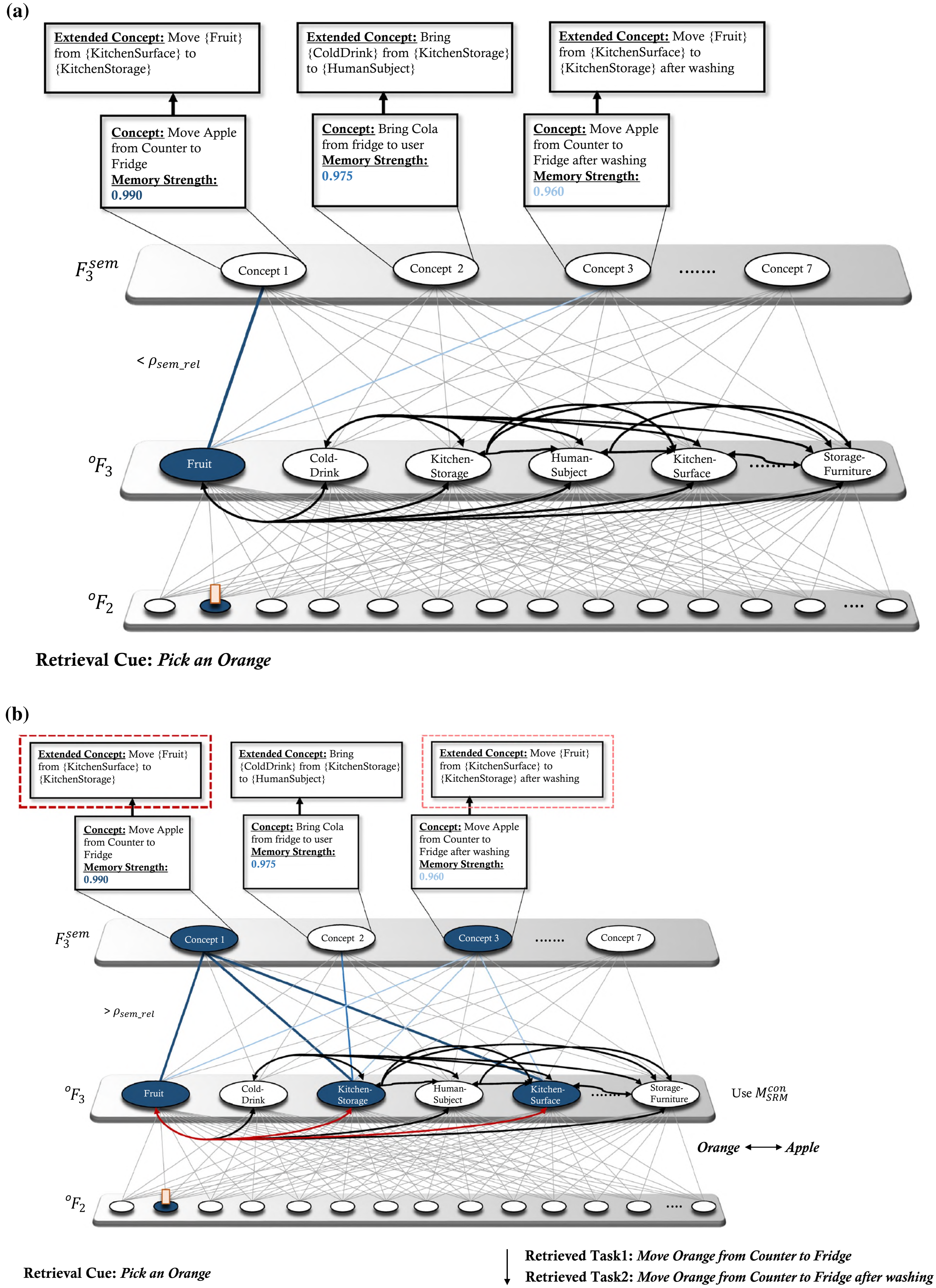

Fig. 4 **a**, **b** Highlight how the task *Move Orange from Counter to Fridge* is retrieved for a partial cue by making use of T_{SRT}^{con}

of consolidation has been evaluated in detail in Nasir et al. (2018). Out of the 76 cues, 26 were constructed by making all possible replacements for objects in episode 1 and associated object categories. Cues such as *Move banana from slab to shelf*, *Move apple from table to cupboard* etc were used. Similarly, cues 11, 26, 8, and 5 associated with episodes 2, 3, 4, and 5, respectively, were used.

As mentioned above, for each of these cues, relevant objects were replaced to test if planning on one instance of an object category enables pMM-ART to extend the planning for the entire category. A few examples of cues used included *Bring cider from cupboard to the user*, *Arrange a spherical toy on NotKitchenCounter*, and *Move orange from counter to shelf after washing it*. We observed that pMM-ART was able to use the relationship between the consolidated episodes and object categories to extend planning for object categories. Hence, it retrieved sequences of events successfully for all 81 cues after learning only 5 tasks and planning for only 9 objects, instead of 29 objects.

Since the initially learned concept *Move Apple from Counter to Fridge* is now extended to *Move Fruit from KitchenSurface to KitchenStorage*, we call it an extended concept as in Fig. 4. In the case of cues like *Move Banana from Table to Shelf*, event sequences for two learned tasks (Episode 1 and Episode 3) were retrieved but in descending order of priority. Thus, the sequence for *Move Banana from Table to Shelf after washing* was also retrieved but its priority was lower because of the low importance associated with the event of washing the fruit. Hence, lower overall memory strength of the task lead to a weaker activation value between ${}^{o}F_3$ and F_3^{sem}. In cases when multiple concepts are retrieved, a user can select whichever sequence of events the user would want the autonomous agent to follow.

7.2.2 Retrieval with partial cues

pMM-ART also has the ability to retrieve in the case where there are partial cues with objects without a context (not in F_3^{epi}). It may or may not exploit the information in T_{SRT}^{con} by making use of the strongest relationship each currently active category has with other category/categories. In cases when the information regarding objects in the retrieval cues does not activate enough categories in ${}^{o}F_3$ to activate a consolidated episode in F_3^{sem}, the vigilance criterion $\rho_{sem-rel}$ is not met. In such situations, a category/categories having the highest concept semantic relation value with each of the currently active category is/are activated. Together, they may or may not be able to activate a semantic concept. We used a total of 36 cues with the first 5 cues being complete cues for the learned tasks and the remaining 31 being partial cues with information about a maximum of two objects. 11 out of 31 times, pMM-ART used T_{SRT}^{con} to aid in retrieval of a possible sequence of events. For the remaining 20 cues, the activated categories were able to meet the vigilance criterion $\rho_{sem-rel}$ and so T_{SRT}^{con} was not used. An example of retrieval with partial cue using T_{SRT}^{con} is shown in Fig. 5a, b. The partial cue *Pick an Orange* is unable to activate any node in F_3^{sem} as shown in Fig. 5a. Hence, using T_{SRT}^{con}, *KitchenStorage* and *KitchenSurface*, having the highest V_A^{con} value, are activated, which together are able to activate concept no. 1 (Fig. 5b). Suitable replacement of apple with orange is also done.

7.3 Case III: Other types of Cues

In this subsection, we tested the ability of pMM-ART with a more diverse range of cue types.

7.3.1 Cues with one or more objects and an event/sequence of events unknown to episodic memory

These types of cues included either (1) one or more objects and an event unknown to episodic memory or (2) one or more objects and the entire sequence of events unknown to episodic memory. This would then include cues for tasks like *Bring Cola from a NotKitchenCupboard*, *Arrange Rectangular toys on Counter*, and *Move Apple from Fridge to Counter*. We used 30 cues that were a combination of *Move Apple from KitchenStorage/HumanSubject to KitchenStorage/KitchenSurface/HumanSubject*. Even though at least one instance from the object categories involved in each of these 30 cues is known to episodic memory, to plan all of these tasks, a sequence of events is required that is not similar to the one that was used for *Move Fruit from KitchenSurface to KitchenStorage*. In such cases, when the sequence of events needs to be changed, pMM-ART is not able to plan the exact new sequence of events. Nevertheless, it still predicts the closest sequence of events to the asked task. For example, for *Move Apple from Cupboard to Counter* it predicted the sequence of events for *Move Apple from Counter to Cupboard*. The new task can be taught to the memory model if needed. We also used 18 cues for *Move Square Toys from KitchenSurface to Surface*. Since no relation existed between these three categories, both in terms of shared concepts and attributes, there was a failure to retrieve any semantic concept from F_3^{sem}. In such a situation, T_{SRT}^{con} was used to activate additional relevant categories with the strongest relation with respective categories. It led to retrieval of more than one concept in descending order of priority.

The property of predicting the closest known sequence of events helped in reducing errors in cases when a cue had erroneous information regarding any one of the objects. Any cue (9 possible cues) of the form *Bring ColdDrink from StorageFurniture* led to a retrieval of a sequence of events for *Bring ColdDrink from KitchenStorage* that is actually correct.

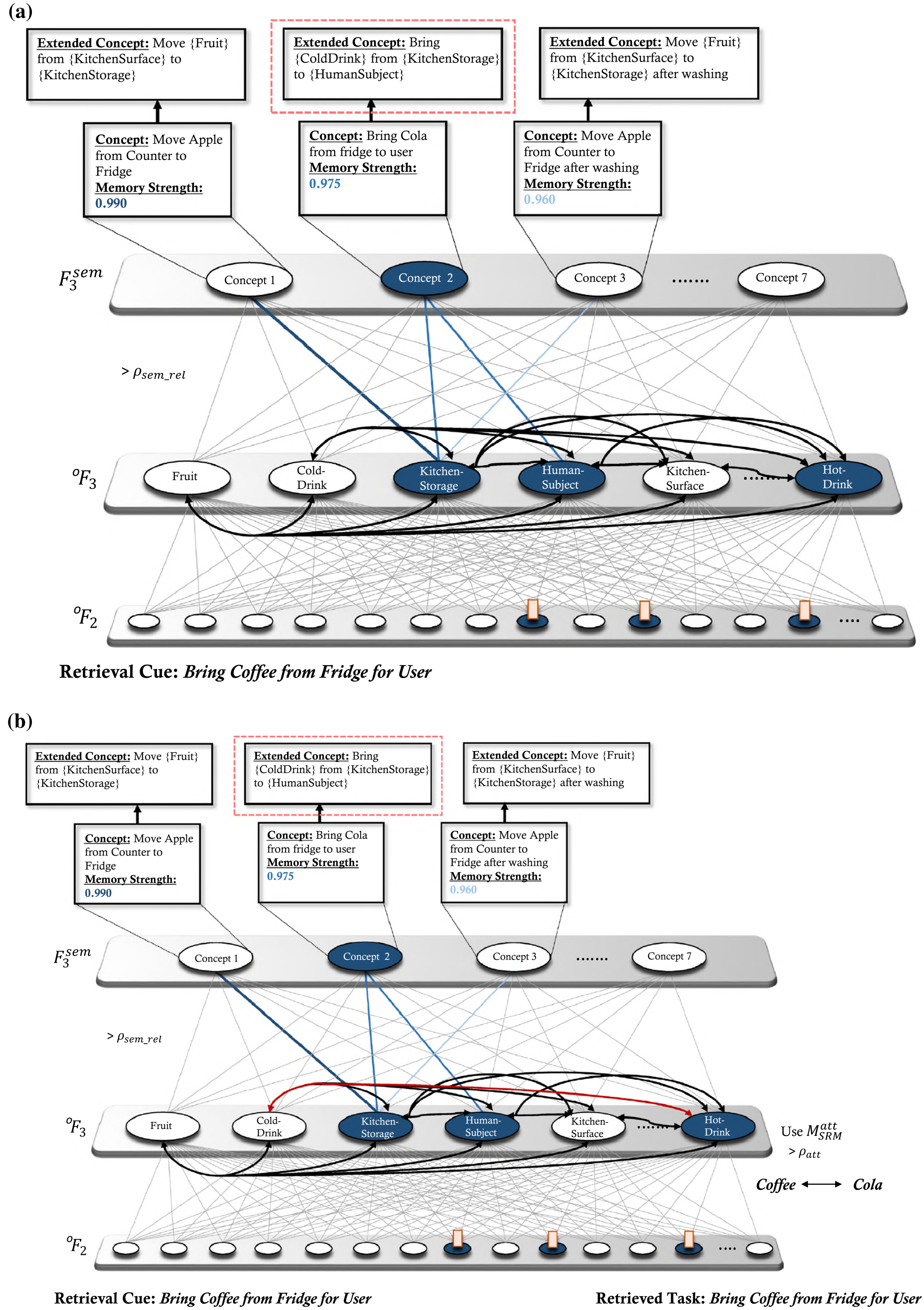

Fig. 5 **a**, **b** Highlight how the task is retrieved for a retrieval cue *Bring Coffee from Fridge for User* by making use of T_{SRT}^{att} even when $\{HotDrink\}$ has no weighted connections with F_3^{sem}

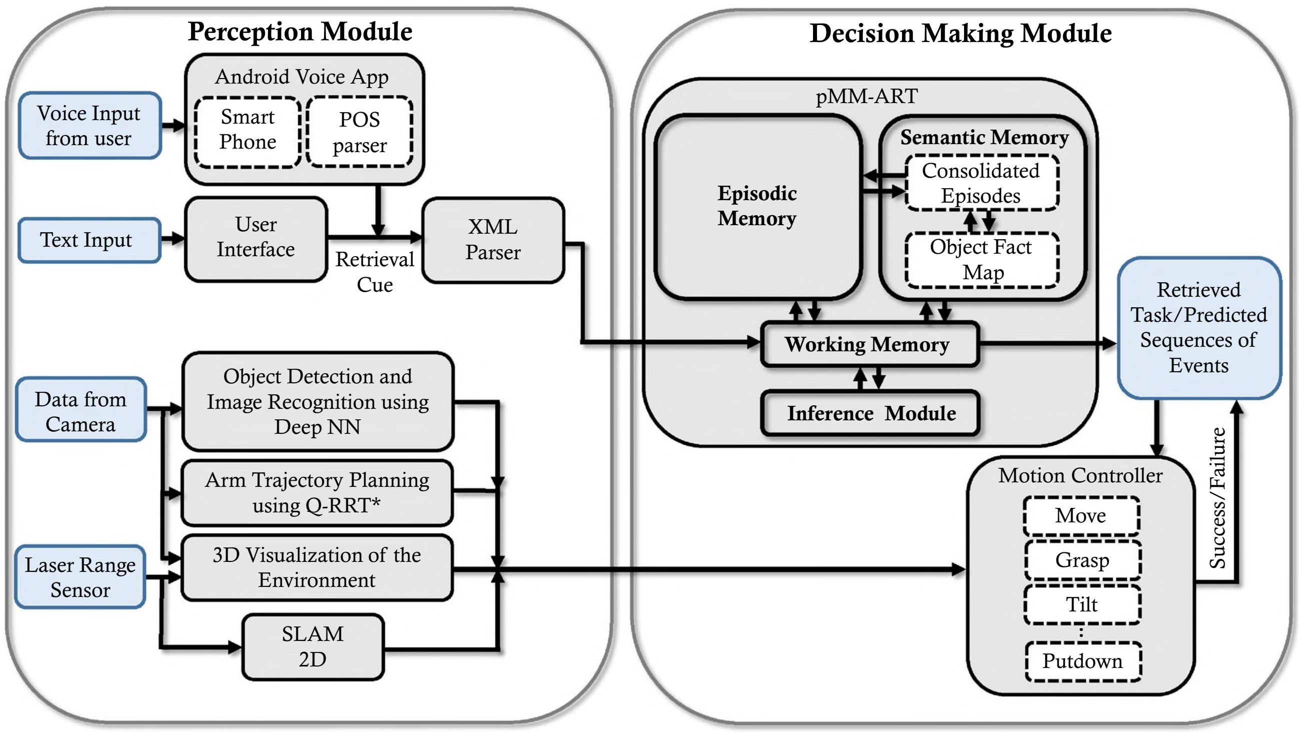

Fig. 6 Control architecture used for experiments on Mybot

7.3.2 Cues with an object category and an event/sequence of events unknown to episodic memory

We also tested a few cues consisting of an entire object category unknown to the episodic memory. This was done to evaluate how pMM-ART would make use of T_{SRT}^{att}. For this, we used two sets of cues (18 cues for each set) defining the tasks *Bring HotDrink from KitchenStorage to HumanSubject* and *Move HotDrink from KitchenSurface to KitchenStorage*. Although there were no weighted connections between the category *HotDrink* and F_3^{sem}, information about other categories in both sets of cues was able to predict the closest sequence of events to the task in question, i.e., *Bring ColdDrink from KitchenStorage to HumanSubject* and *Move Fruit from KitchenSurface to KitchenStorage*. Now the $V_{\lambda_1=2,\lambda_2=3}^{att}$ value between categories *ColdDrink, HotDrink* turned out to be close to 1 as they shared the properties *Sustenance, Drinkable, Kitchen* satisfying the vigilance criterion ρ_{att}. Hence, pMM-ART was able to plan for *Bring HotDrink from KitchenStorage to HumanSubject* as shown in Fig. 5a, b. In the case of *Move HotDrink from KitchenSurface to KitchenStorage*, $V_{\lambda_1=1,\lambda_2=3}^{att} = 0.667$ was less than ρ_{att}. Therefore, it simply retrieved cues for the closest task it knew (*Move Fruit from KitchenSurface to KitchenStorage*) showing the lack of a plan available for this scenario. In summary, the need for learning a possible sequence of events defining a relationship between {*coffee, milk, tea*}, {*Counter, Slab, Table*} and {*Fridge, Cupboard, Shelf*} was observed since T_{SRT}^{att} failed to retrieve the plan. Of course, if ρ^{att} was set lower, the result would have been different.

In addition to the above mentioned scenarios, if a particular object is not found at the expected location, the inference system can be used to choose another object from the same category present at the expected location. Using OFM, this would be possible without the need for hierarchical semantic labeling for objects in an RGB-D image like in Wu et al. (2014) and instead flat labeling can be used.

8 Experiment on Mybot

The model was also validated on Mybot, a robot developed in the Robot Intelligence Technology (RIT) Lab at KAIST. Mybot makes use of Odroid XU board, Ubuntu 14.04 and ROS.

The head, which has 17 degrees of freedom (DOF), consists of an RGB-D Camera and a thermographic sensor that are used together to detect and recognize the objects in the environment. If the robot is not able to see the required object in the present view, it moves its head left and right in search of those objects making use of its neck, which has 3 DOF. Mybot has a total of 22 DOF in its upper body (10 DOF in each arm and 2 DOF in the torso). The lower body of Mybot is a mobile base that has differential wheels with wheel speed of about

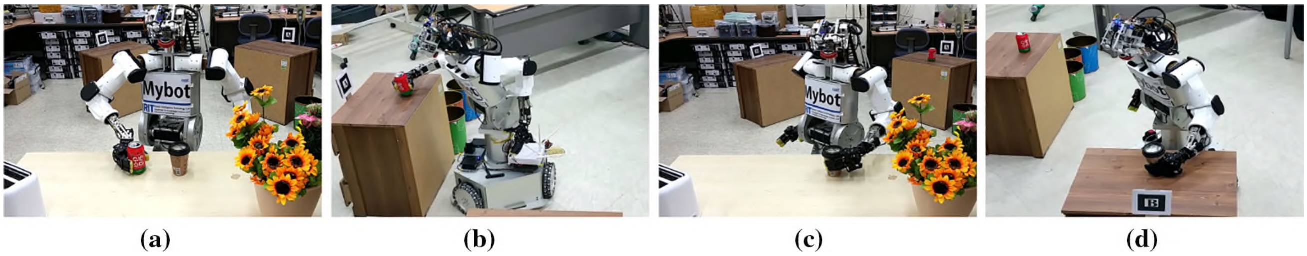

Fig. 7 **a**–**d** Mybot performing two tasks of arranging Cola and Coffee in CabinetA and CabinetB, respectively. The sequence of events for these two tasks were already taught to Mybot

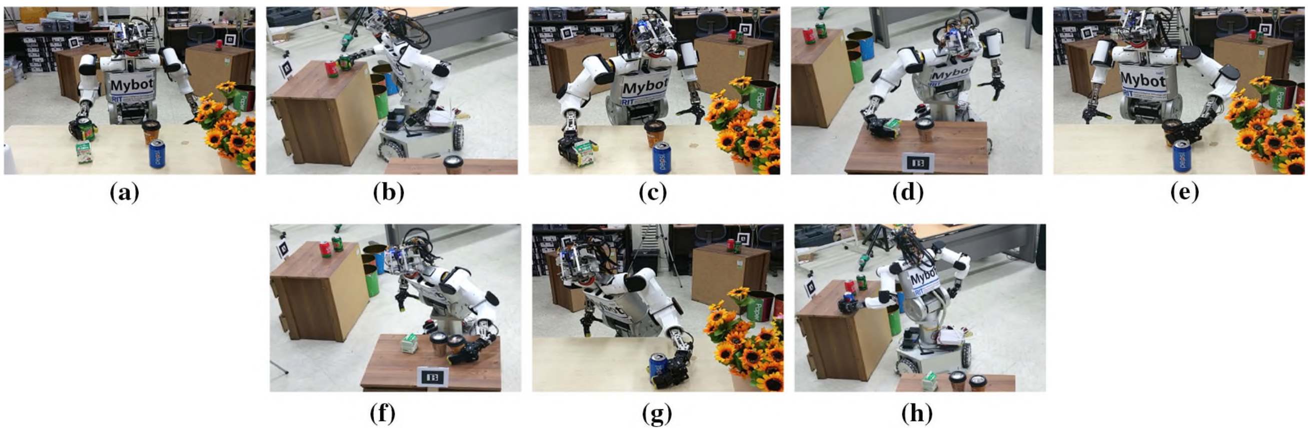

Fig. 8 **a**–**h** Mybot performing four tasks of arranging Cider, Milk, Tea, Pepsi in correct cabinets. The sequence of events for these tasks were not taught to Mybot

2.0 m/s. Moveit! package (Sucan and Chitta 2011) along with a laser range sensor URG-04LX-UG01 is used for generation of the 3D map of the environment. The mobile base Mybot-KSR2 uses the ROS open-source package GMapping[1] for simultaneous-localization and mapping (SLAM) with its laser range sensor. For trajectory generation of the arms, Q-RRT* (Jeong et al. 2015) is used which provides faster real time planning as compared to RRT*.

Figure 6 highlights the control architecture used to carry out the experiments. We made Mybot learn a total of six episodes which included: *Arrange Cola in CabinetA*, *Arrange Coffee in CabinetB*, *Bring Cola from Counter to Table and pour it in a Cup*, *Arrange RedCircularToy in BoxA*, *Arrange RedSquareToy in BoxF*, and *Arrange RedRectangularToy in BoxC*. Similarly, a total of 12 categories were learned by the robot including {*ColdDrink = Cola, Pepsi, Cider, HotDrink = Milk, Tea, Coffee, Surfaces = Table, Counter, DrinkingContainers = Cup, Mug, ColdDrinkStorage = CabinetA, HotDrinkStorage = CabinetB, CircularToys = RedCircularToy, GreenCircularToy, BlueCircularToy, SquareToys = RedSquareToy, GreenSquareToy, BlueSquareToy, RectangularToys = RedRectangularToy, GreenRectangularToy, BlueRectangularToy, CircularToysStorage = BoxA, SquareToysStorage = BoxF, RectangularToysStorage = BoxC*}.

Once the episodes and categories are learned, the user sends in a command by voice/text interface that, after being analyzed, is sent from the perception module to the decision-making module. Here the inference module makes a decision about passing the command to episodic or semantic memory based on the type of object information it found in the user command. pMM-ART then predicts a task (sequence of events) required for fulfilling this user command. The sequence of events are sent one by one to the motion controller. Other sensory data, i.e., information about the environment, calculated arm trajectories etc., are also received by the motion controller, which executes an event and returns success if the event has been executed successfully. In this way, the entire task is executed.

We sent commands asking for exactly the same tasks that it learned. Mybot was able to perform each of those six tasks (task one and two can be seen in Fig. 7). Then, we validated pMM-ART by sending in commands including *Arrange Pepsi*, *Arrange Milk*, *Arrange Cider*, and *Arrange Tea* to see if it could extend a learned plan for an object to an entire category of objects. Note that these retrieval cues only included partial information. The cues did not include the information about which cabinet a particular drink needs to be arranged in. That was calculated by pMM-ART making

[1] http://wiki.ros.org/gmapping.

use of T^{con}_{SRT} and all the tasks were executed successfully as shown in Fig. 8. A video is also available (Online Resource (1). Due to space constraints, we summarized the results of one of the experiments, which included two tasks of putting *Cola* and *Cider* in *CabinetA* and *CabinetB* respectively, and then extending this knowledge to other drinks. More details on the experimental setup can be found in Nasir and Kim (2016).

9 Conclusion

Keeping in consideration the advantages of having interactions between episodic and semantic memories, this paper proposed a mechanism to enhance the capabilities of autonomous agents by making use of a semantic hierarchy and its relationship with learned episodic memories that get consolidated over time. This allows for category-based planning rather than object based planning. Also, using T^{con}_{SRT} and T^{att}_{SRT}, it extends a learned plan for similar categories and categories without any context, which allows for inter-category object replacements.

Even though pMM-ART looks to be a promising model, it has its limitations in the current form. For example, when the same group of objects is associated with more than one concept, all of those concepts are retrieved in order of priority regardless of what the incoming retrieval cue is. Hence, there is a need to understand the "conceptual meaning" of a retrieval cue. For example, both the retrieval cues *Move Apple from Counter to Fridge* and *Move Apple from Fridge to Counter* include the same objects but the sequence of tasks required for both is different. In addition, if the semantic similarity is very high between two categories, all the previously learned concepts associated with a category may be adapted for objects in the second category. This generalization may not always be correct. We look to work on these limitations in the future versions of the proposed model. Lastly, we would like to automate the process of setting the pMM-ART parameters for making the system robust so that it is easier to adapt it in various contexts. We also plan to evaluate it on a comprehensive dataset and adjust the parameters by means of cross-validation.

Acknowledgements This work was supported by the National Research Foundation of Korea (NRF) Grant funded by the Korea (MSIP) (No. NRF-2014R1A2A1A10051551) and the Technology Innovation Program, 10045252, funded by the Korea MOTIE. The authors would like to thank Yong-Ho Yoo for his guidance during experiments on Mybot. The authors would also like to thank Jennifer Olsen, a post-doc at Computer–Human Interaction in Learning and Instruction Lab., for her feedback on the draft.

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