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User Preference-Based Dual-Memory Neural Model With Memory Consolidation Approach

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***Abstract*— Memory modeling has been a popular topic of research for improving the performance of autonomous agents in cognition related problems. Apart from learning distinct experiences correctly, significant or recurring experiences are expected to be learned better and be retrieved easier. In order to achieve this objective, this paper proposes a user preference-based dual-memory adaptive resonance theory network model, which makes use of a user preference to encode memories with various strengths and to learn and forget at various rates. Over a period of time, memories undergo a consolidation-like process at a rate proportional to the user preference at the time of encoding and the frequency of recall of a particular memory. Consolidated memories are easier to recall and are more stable. This dual-memory neural model generates distinct episodic memories and a flexible semantic-like memory component. This leads to an enhanced retrieval mechanism of experiences through two routes. The simulation results are presented to evaluate the proposed memory model based on various kinds of cues over a number of trials. The experimental results on Mybot are also presented. The results verify that not only are distinct experiences learned correctly but also that experiences associated with higher user preference and recall frequency are consolidated earlier. Thus, these experiences are recalled more easily relative to the unconsolidated experiences.**

***Index Terms*— Adaptive resonance theory (ART), cognition, consolidation, episodic memory, semantic-like, user preference.**

I. Introduction

DECLARATIVE memory, one of the two types of long-term human memory, is basically the memory of events and facts. It refers to those memories that can be consciously and explicitly recalled or declared [1]–[3]. Declarative memory can then further be divided into episodic memory and semantic memory. Episodic memory refers to the memory of personal experiences and specific events in time in a serial form, whereas semantic memory is a structural record of facts, meanings, and concepts that have been acquired over time [4]–[6].

Many studies highlight the importance of hippocampus [7], [8], an area of brain which is considered to be the place of episodic memory, as being very critical for representing relationships between stimuli and forming memories associated with temporally dated, spatially located, and personally experienced events or episodes [9], [10]. Episodic memory is considered to be of crucial significance for various cognition related activities [12], [13]. Also, studies reveal that emotionally arousing experiences are generally well remembered [14], [15]. More precisely, emotions enhance the encoding of emotional experiences into our memory by influencing attention and perception [16]. Emotions and attention at the time of encoding seem to play an important role in enabling the significance of an experience to regulate the strength of memory of the experience [17], [18]. In light of the role that memory plays in improving the cognitive abilities generally, one of the most critical components for an autonomous robot would be to remember its experiences and recall them later. Not just that, in terms of artificially intelligent agents, the aforementioned information [14]–[18] that certain experiences are encoded more strongly than others can also be used in various ways to enhance the cognitive skills of a robot. One way to take advantage of this would be by developing a memory model that enables itself to strongly encode and easily recall those experiences them that are deemed significant by the user or the robot itself while adapting to the ever-unpredictable world.

Also, it is reasonable to argue that experiences that are repeated frequently must not require the same level of detailed or error-free cues to being recalled after a certain number of times being recalled. Instead, over a period of time, the recurring experiences must be predicted earlier and with more ease compared with when they were learned for the very first time. In other words, those memories should become more stable and easier to recall. This follows loosely the concept of memory consolidation in biological brains where an unstable memory trace is converted into a stable form that is resistant to degradation over subsequent days to years [19].

This paper, taking inspiration from the biological brain, but without trying to replicate the biological memory system or consolidation process, extends a spatiotemporal memory model episodic memory adaptive resonance theory (EM-ART) into a memory model that tries incorporating the aforementioned abilities to develop a robust mechanism for recalling episodic memories. Our model user preference-based dual-memory adaptive resonance theory (pDM-ART) learns and forgets memories at various learning rates that are defined by a parameter that we termed as the importance parameter I. Although I can be used to define anything the user might want the episodic memory to be adapted to, in our model, I is

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defined as user preference, which indicates how significant a particular event or episode is to the user. It should be noted that our work focuses on the effect of a "user preference" parameter on the memory of an autonomous robot/service robot and not on the modeling of the parameter itself. Second, episodic memories undergo a consolidation-like process to form a semantic-like memory component. Our semantic-like memory component consists of consolidated episodes that are easier to recall and are more stable compared with the unconsolidated episodes in episodic memory. Thus, it facilitates the retrieval of episodic memories by adding another route for retrieval. The timing of consolidation for a particular episode is dependent on the associated I value and the frequency of recall of that experience.

Section II presents related work, while Section III describes a brief summary of the proposed pDM-ART network. Section IV discusses encoding and learning of episodes using pDM-ART. Retrieval and memory consolidation are discussed in Section V. Section VI analyzes the space and time complexity, while Section VII evaluates our approach in detail, along with the comparative results using EM-ART for various types of retrieval cues, demonstrating the usefulness of the approach. The experimental results on Mybot are presented in VIII, followed by concluding remarks that follow in Section IX.

II. Related Work

For empowering robots with higher levels of autonomy, various cognitive architectures with declarative memory have been proposed [20]–[22]. These also include various symbolic [13], [23], [24] and bioinspired [25]–[27] episodic memory models, which differ in their mechanisms used for storing and retrieving. A number of neural network models have also been developed for sequential learning, which can be employed for episodic memory. Some of these include spatiotemporal memories for machine learning [27], long–short-term memory [28], temporal sequential learning [29], associative neural networks for spatiotemporal learning [30], anticipation-based temporal pattern generation [31], anticipation-based temporal sequence learning [32], and hierarchical temporal memory [33]. Generally, in bioinspired approaches, neural models that learn spatiotemporal sequences directly from experienced situations are employed providing a more efficient way of categorizing events.

Adaptive resonance theory (ART) network, introduced by Carpenter and Grossberg [25], is a self-organizing neural network model that is able to categorize patterns and is well suited to problems that require online learning of large evolving databases. A neuromimetic episodic cognitive model is presented by Taylor *et al.* [34], which makes use of fuzzy ART [35] and temporal integration to form episodic representations. In [36], unlike [34], recall methods have also been devised enabling the selection and retrieval of the episodes. It is an extension of a TopoART [37] neural network that incorporates temporal information in the input space to form episode-like clusters.

The recently proposed EM-ART model [38], based on a generalization of fusion ART [39], stands out because of its ability to store the spatiotemporal relations among various events and retrieve them with a higher tolerance toward noise compared with the prior models of spatiotemporal memory. In [40], a reward strategy has been developed to improve the retrieval accuracy of EM-ART in situations where the lengths of the learned episodes vary significantly. Varied episode lengths can lead to an incorrect recall of an episode when the retrieval cue is incomplete.

Also, recent research has proved the interdependence of both memory systems by pointing out the significant overlap between episodic and semantic memories essential for retrieval of autobiographical memories, episodic learning, and semantic processing [12], [41], [42]. Although not many bioinspired consolidation approaches for episodic memory have been proposed for autonomous agents, a few recent contributions employ ART in their schemes. Wang *et al.* [43] developed a memory module, employing fusion ART networks, which learns both declarative and procedural knowledge. In the declarative memory module, the episodic memory is built with the same approach as in [39], while semantic knowledge is built through a memory consolidation process in which episodes from the episodic memory model are played back to gradually extract and learn general facts, using a lower template matching threshold. In this approach, each type of semantic memory can be built using fusion ART with each input field representing an attribute or property of a concept. This system employs playing back of episodes for the knowledge transfer process.

Gao and Tan [44] designed a multimemory model activities of daily living (ADL) ART to discover the daily activity pattern of a sensor monitored user from his/her ADL. The daily activity patterns are encoded in episodic memory using EM-ART and the patterns are consolidated into semantic memory by extracting the regularities of the activity routines. This system uses a date input field indicating the date information as tags.

In another adaptation of the EM-ART network, Leconte *et al.* [16] incorporated the emotional influences of a robot to categorize and recall its experiences. Their adaptation dynamically sets the learning rate and vigilance parameters, two of the key parameters of EM-ART, based on how the robot is able to carry out its tasks using a simple artificial emotion model. One objective of their model is to provide a fast recall of those experiences of the robot that are associated with emotions.

The models in the above-mentioned literature, to the best of our knowledge, are able to represent and learn spatiotemporal sequences. Before going into the formal description of the proposed model, we would like to highlight the ways in which it relates to and differs from some of the existing models.

1) Just like AEM-ART [16], LTM [27], and EM-ART [32], [38], our model also comprises of a hierarchical network architecture.
2) However, unlike [16], [27], [38], [43], and [44], the learning rate and memory strength of each event/episode is biased by a "user" input/preference at the time of encoding.

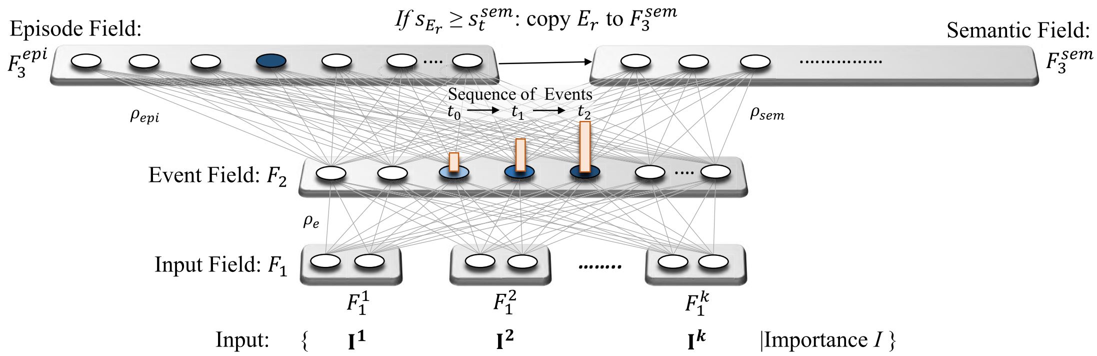


Fig. 1. Architecture of the proposed pDM-ART network, where s_{E_r} and s_t^{sem} represent the memory strengths for an rth episode E_r and the semantic memory threshold value, respectively.

3) Even though [16], [27], [38], and [45] support retrievals based on degraded cues, pDM-ART provides a consolidation mechanism that results in an alternate route that may facilitate retrieval with further degraded cues for those spatiotemporal sequences that are recurrent and significant to the user.
4) Moreover, the influence of an external parameter on the learning rate is also employed in [16], but that external parameter models the emotions of the robot at the time of learning and the learning rate is changed (increased/decreased) for any future learning of similar experiences, while in our model, the learning rate is increased/decreased based on a user input for the current representation, as well as similar future representations that may activate the current representation.
5) Unlike [43], memory consolidation is online (does not require specific playback of the episodes in episodic memory) and leads to representations that still represent spatiotemporal knowledge, facilitating the retrieval of recurrent or significant experiences in episodic memory.

Because the two schemes (the scheme in [43] and our proposed pDM-ART) differ in that they both have different meanings of their semantic memories and the consolidation processes, a direct comparison is not feasible; hence, it is not covered in this paper.

III. Summary of Proposed pDM-ART

This section summarizes the proposed model, pDM-ART. The proposed model makes two contributions. First, it provides a mechanism where a user preference is incorporated in the memory model as an importance factor I associated with each event that the robot experiences. The higher the importance associated with an event, the stronger the encoding is compared with other events at time of encoding. Second, pDM-ART encourages a consolidation-like process to ensure that significant memories and recurrent memories are distinguished from insignificant and nonrecurring memories. Experiences/episodes become more stabilized, which means they allow adaptation to partial sequences and changes in event representation and sequence, and are easier to recall. The point at which an episode is consolidated is dependent on the importance associated with the events experienced in that particular episode and the recall frequency of that episode. Episodes that are strongly encoded and frequently retrieved are consolidated earlier.

Fig. 1 shows the overall architecture describing the dynamics of the proposed pDM-ART. The importance factor leads to various learning rates and various forgetting rates for events and episodes from input layer F_1 to event layer F_2 and from event layer F_2 to episode layer F_3^{epi}. An event has the general representation as *Event*: $\{\mathbf{I}^1, \mathbf{I}^2, \ldots, \mathbf{I}^l|$ Importance $I\}$, where $\mathbf{I}^k$ represents an input vector to channel k, $k = 1, 2, \ldots, l$ is the index of the input channels, and I is the importance associated with the event. Note that I does not have its own channel at the input layer rather it is concatenated along with the input vector. Each channel here represents the key information regarding the situation experienced by the autonomous agent, such as *what*, *where*, and *how*.

The input $\{\mathbf{I}^1, \mathbf{I}^2, \ldots, \mathbf{I}^l|$ Importance $I\}$ is fed at input layer F_1 and $\{\mathbf{I}^1, \mathbf{I}^2, \ldots, \mathbf{I}^l\}$ is encoded as an event at layer F_1 to F_2. I is responsible for controlling parameters like learning rate and contribution factor at the time of learning of $\{\mathbf{I}^1, \mathbf{I}^2, \ldots, \mathbf{I}^l\}$ from F_1 to F_2. The learning rate defines the amount of effect a pattern has on the changes in the weights of an existing pattern, whereas the contribution factor defines the contribution of a channel's attributes. A sequence of events is learned as an episode at F_3^{epi}, while F_3^{epi} and F_3^{sem} represent the episodic and semantic-like memories, respectively. In our memory model, semantic memory refers to those memories that are consolidated based on retrieval frequency and associated significance. Similarly, I also controls learning rate and contribution factor from F_2 to F_3^{epi}. In this way, the importance factor I is embedded in the memory model, eventually effecting the retrieval success in various scenarios as will be seen in the later sections.

Each jth event and rth episode is associated with a memory strength value s_{e_j} and s_{E_r}, respectively. If the memory strength s_{E_r} of an rth episode E_r increases above a semantic memory threshold value s_t^{sem} defined by the user, the episode E_r is copied into the semantic-like memory component. Also, the higher the recall frequency, the higher the chances for the episode to be consolidated. In other words, all episodes, if not forgotten, are consolidated with a rate proportional to the factor I associated with them and their recall rate. Memories

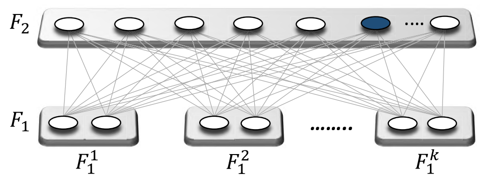


Fig. 2. Fusion ART architecture.

with high I and high recall frequency have the highest chance of consolidation. Once the semantic-like component is formed, there are now two routes, both with different thresholds, ρ_{epi} and ρ_{sem} for the template matching process to allow the retrieval of an episode.

IV. Encoding and Learning of Episodes

Since pDM-ART is based on EM-ART [38], which is built by hierarchically joining two multichannel self-organizing fusion ART neural networks [39] to learn and retrieve a temporal sequence of events called an episode, we first describe the dynamics of fusion ART for better understanding. The basic structure of fusion ART is shown in Fig. 2.

A. Fusion ART

Fusion ART network [39] is an extended model of ART [25], which is used to learn individual events encoded as weighted connections between the input layer F_1 and the event layer F_2.

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 ith input to channel k, $k = 1, 2, \ldots, l$. 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, $\bar{\mathbf{I}}^k = (1 - \mathbf{I}^k)$. In our implementation, we did not use complement coding as it leads to incorrect retrieval when a large number of events and episodes are learned.

2) Parameters: Each of the field dynamics is 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) 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 jth node in F_2 for learning the input pattern in F_1^k, α_k is the choice parameter, and γ^k is the contribution parameter. Also, $k = 1, 2, \ldots, l$ is the number of input channels, $\wedge$ represents 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 the norm operator is defined by $|\mathbf{a}| = \sum_{i=1}^{D} |a_i|$.

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 as 1 and all the other outputs are set as 0.

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 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

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

In order for resonance to occur, (4) should be true, that is, the match value of the selected node J should be greater than the vigilance parameter ρ^k. The vigilance parameter ρ^k sets a threshold for the template matching step. If (4) is not true, 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.

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

$$\mathbf{w}_J^{k(\text{new})} = (1 - \beta^k)\mathbf{w}_J^{k(\text{old})} + \beta^k\left(\mathbf{x}^k \wedge \mathbf{w}_J^{k(\text{old})}\right). \tag{5}$$

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 $\mathbf{x}^{k(\text{new})} = \mathbf{w}_J^k$.

B. Encoding and Learning in pDM-ART

A vital part of episodic memory is to encode the sequential or temporal order between events. The EM model, an adaptation of which we have proposed, provides this ability of associating and grouping patterns across time by joining hierarchically two fusion ART networks [38].

The learning phase for episodic memory of pDM-ART is illustrated in Fig. 3. An activity vector $\mathbf{x}^k$ of input layer F_1 undergoes four steps to learn an event node in event layer F_2. The activation values are calculated using (1) for each event node to find a potential match for the activity vector $\mathbf{x}^k$. In accordance with code competition highlighted by using (2), the event node with the highest activation value is chosen for template matching. The match value returned by using (3) determines how close the node with highest activation value is to the activity vector. If the match value is higher or equal to the vigilance parameter ρ^k, resonance is said to occur, the node is selected as the current event node, and the activity vector $\mathbf{x}^k$ is learned by modifying the weights as in (5). On the other hand, if resonance fails to occur, a new event node is created to encode the new pattern.

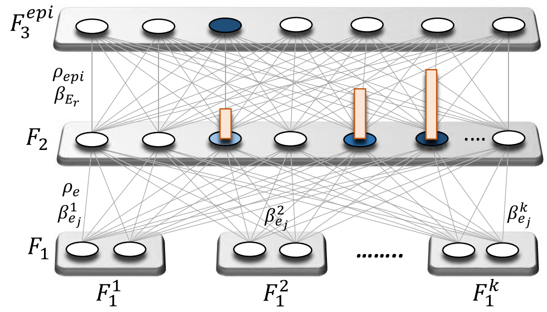


Fig. 3. pDM-ART episodic memory learning phase where β_{e_j} and β_{E_r} represent the learning rates for jth event e_j and rth episode E_r, respectively.

The activation values of the situational attributes are held in F_1 layer. The pattern of activations in F_1 layer forms the basis of selection and activation of a node in F_2 layer, which is considered as the recognition of an event once the resonance occurs. Updating the weights in the connections between F_1 and F_2 layers leads to the learning of the incoming event based on β_{e_j}, where β_{e_j} is the learning rate for jth event. Using the same dynamics, as used for learning an event from F_1 to F_2, a temporal sequence of events is learned from F_2 to F_3^{epi}. In F_2 layer, a decaying pattern of activations is produced by a sequence of events. This pattern of activations represents an episode that is also learned as the weighted connections between F_2 and the category selected in F_3^{epi}. The activation values of nodes representing an event are used to represent the time sequence of the events. The most recently activated node is given a value of 1, while the nodes that were selected previously are decayed over time using a decaying factor, given by $\tau \in (0, 1)$.

An event including an action input $\mathbf{I}^1$, an object input $\mathbf{I}^2$, and an importance I is represented by *Event*: $\{\text{Action}(\mathbf{I}^1), \text{Object}(\mathbf{I}^2)|\ \text{Importance}\ I\}$. The user preference then controls the learning rate and the contribution factor for each event during learning from layer F_1 to F_2 and consequently for each episode that is formed from F_2 to F_3^{epi}, where F_3^{epi} refers to the episodic memory component in layer F_3.

The contribution factor and learning rate from F_1 to F_2, for every jth event e_j, change according to the following rules:

$$\gamma_{e_j} = \gamma_{\min} + (1 - \gamma_{\min})(I_{e_j} - 0.5) \tag{6}$$
$$\beta_{e_j} = \beta_{\min} + (1 - \beta_{\min})(I_{e_j} - 0.5) \tag{7}$$

where γ_{e_j}, $\gamma_{\min} \in [0.5, 1]$, and $I_{e_j} \in [0, 1]$ represent the contribution factor for event e_j, the minimum contribution factor of the memory model initially set, and the importance of the event e_j, respectively. Furthermore, β_{e_j} and $\beta_{\min} \in [0.5, 1]$, respectively, represent the learning rate for event e_j and the minimum learning rate of the memory model initially set.

The contribution factor γ_{E_r} and learning rate β_{E_r} from layer F_2 to F_3 are also defined by the same equations for an rth episode E_r, except that I_{e_j} is replaced by

$$I_{E_r} = \frac{\sum_{j=1}^{p} I_{e_j}}{p} \tag{8}$$

Algorithm 1 pDM-ART Episodic Learning

BEGIN
ASSIGN user preference I_{e_j} for every event e_j in episode E_r
CALCULATE initial memory strength $s_{e_j}^{init}$ for e_j based on I_{e_j}
FOR every subsequent event e_j in episode E_r
Based on input I_k in F_1, select a resonant node J in F_2
Let node activation y_J be 1 or any predefined maximum value
FOR every previously selected node j in F_2
Let its activation be $y_j^{new} = y_j^{old}(1 - \tau)$ or 0 if $y_j^{old} \leq 0$
After a subsequent presentation of E_r, given an activation vector y formed in F_2
Select a resonant node R in F_3^{epi} on the basis of the activation vector y
if E_R is a novel episode, learn its associated weight vector $w_R^{(new)} = y$ **then**
    Set I_{E_R} for episode E_R based on (8)
    CALCULATE $s_{E_R}^{init}$ for E_R based on I_{E_R}
end if
END

where $I_{E_r} \in [0, 1]$ is the importance factor for the rth episode, p is the total number of events in the rth episode, and I_{e_j} is the importance of the jth event in the rth episode. Algorithm 1 outlines the learning procedure in pDM-ART.

V. Retrieval of Episodes and Memory Consolidation

A. Retrieval of Episodes

The events and episodes, once learned by pDM-ART, can be retrieved by a top-down readout procedure. It receives a retrieval cue that can either be complete/incomplete or noisy in terms of event representation or event sequence. A retrieval cue activates a node in F_2. If the match is high enough, the node is recognized as the incoming event. All the incoming events in the retrieval cue are recognized in this way. A similar process takes place from F_2 to F_3 to select an episode that matches the most with the input and also fulfills the vigilance criterion. In this way, an episode is selected and the weights are read out by a top-down process, which takes place first from F_3 to F_2 and then from F_2 to F_1 in a sequential manner by making use of a vector that first complements the values in F_2 such that $\bar{y}_j = 1 - y_j$. Given this complement vector, the weights of the node associated with the highest value are read out first from F_2 to F_1. In this manner, the entire sequence of events is retrieved in the same order in which they were encoded and learned.

A cue for retrieving an event, for example, with an action input $\mathbf{I}^1$ and object input $\mathbf{I}^2$ is represented by *Retrieval cue*: $\{\text{Action}(\mathbf{I}^1), \text{Object}(\mathbf{I}^2)\}$. Before the formation of the semantic-like memory, a retrieval cue activates a memory from the episodic memory component and the weights would be read out if the match is above the threshold vigilance value ρ_{epi} for the episodic component from F_2 to F_3^{epi}.

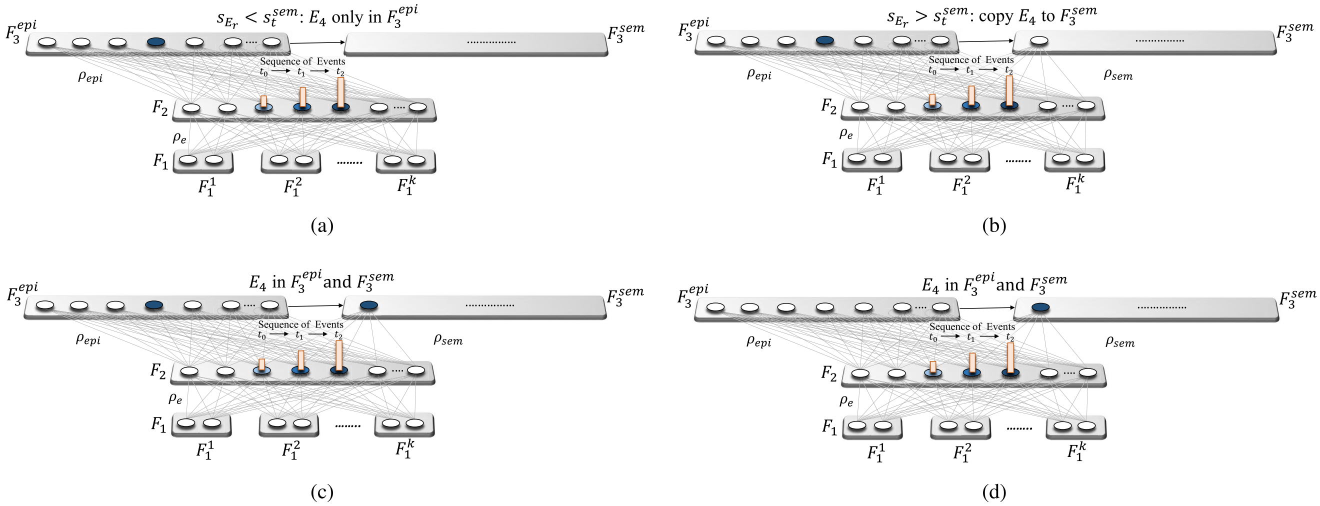


Fig. 4. (a)–(d) Particular episode, in this example E_4, is copied to F_3^{sem} during the retrieval phase. The various retrieval routes that can be taken once the episode is copied to F_3^{sem} are explained.

As the episodes start consolidating, an episode can be activated by either of two routes, one to the episodic memory component and the other to the semantic-like memory component. If neither of the two routes succeeds in providing resonance, retrieval failure is recorded. Both of the 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. As episodes are consolidated in the order of their frequency being recalled, the consolidated episodes probably contain more useful information. Apart from recalling frequency, the user can also control which episodes should move to the semantic memory faster than the others by setting the values for the importance parameter associated with each event. The procedure for consolidation is explained in the following section. To assist fast recall of consolidated episodes, ρ_{sem} is lower than ρ_{epi} to give a more flexible semantic-like component. Also, the learning rate β_{sem} is lower than β_{min} used in episodic learning. This is to keep the consolidated episodes stable in memory, which means that the weights associated with them change slowly over time. The formation of two routes leads to a robust retrieval mechanism as will be observed in Section VII.

B. Memory Consolidation

The proposed memory model assigns a memory strength value to each and every event and episode at the time of encoding based on the importance factor that the user defines. For pDM-ART, the memory strengths for both events and episodes are defined as follows:

1) Memory Strength for Events: The strength of an event e_j at time t is computed depending on if the event is just created or reactivated, otherwise. The strength of an event e_j when e_j is just created at time t, reactivated at time t, and not reactivated at time t is respectively computed as follows:

$$s_{e_j}(t) = \begin{cases} s_{e_j}^{\text{init}} = s_{\min} + (1 - s_{\min})(I_{e_j} - 0.5) & \text{(9a)} \\ s_{e_j}(t-1) + (1 - s_{e_j}(t-1))r_s & \text{(9b)} \\ s_{e_j}(t-1)(1 - \delta_s) & \text{(9c)} \end{cases}$$

where $s_{e_j}^{\text{init}}$ is the initial memory strength of the event e_j, $s_{\min} \in [0.5, 1]$ is the minimum value set initially for the proposed memory model, and $s_{e_j}(t)$ and $s_{e_j}(t-1)$ are the memory strengths of the event e_j at time t and $t-1$, respectively.

2) Memory Strength for Episodes: Similarly, the strength of an episode E_r at time t can be computed depending on if the episode is just created or reactivated, otherwise. The strength of an episode E_r when E_r is just created at time t, reactivated at time t, and not reactivated at time t is, respectively, computed as follows:

$$s_{E_r}(t) = \begin{cases} s_{E_r}^{\text{init}} = s_{\min} + (1 - s_{\min})(I_{E_r} - 0.5) & \text{(10a)} \\ s_{E_r}(t-1) + (1 - s_{E_r}(t-1))r_s & \text{(10b)} \\ s_{E_r}(t-1)(1 - \delta_s) & \text{(10c)} \end{cases}$$

where $s_{E_r}^{\text{init}}$ is the initial memory strength of the episode E_r, $s_{\min} \in [0.5, 1]$ is the minimum value set initially for the proposed memory model, and $s_{E_r}(t)$ and $s_{E_r}(t-1)$ are the memory strengths of the episode E_r at time t and $t-1$, respectively.

Whenever an event or an episode is formed, the initial memory strength is set according to the importance factor as shown by (9a) and (10a), respectively. Therefore, in this way, the initial memory strength may not be the same for all memories. This ensures that two events of unequal importance do not get strengthened or decayed at the same rate. Whenever an event or an episode is reactivated, the memory strength is strengthened proportionally to a reinforcement rate r_s, as in (9b) and (10b). The memory strengths gradually decay by a decay factor δ_s for events and episodes, as in (9c) and (10c).

An event or an episode whose memory strength falls below a threshold value $s_t \in [0, 1]$ is removed from the memory. On the other hand, any event or episode whose memory strength is strengthened above a semantic-like memory threshold value $s_t^{\text{sem}} \in [0, 1]$ is moved to semantic-like memory following loosely the concept of consolidation. Fig. 4 demonstrates how memory consolidation takes place during the retrieval phase. Fig. 4 highlights the details of copying one particular episode, in this example, the fourth episode E_4 to semantic-like memory during the retrieval phase after multiple cues including the events of E_4 are received. It does not matter if a cue for one single episode is received multiples times in a row or multiple times within a combination of cues for other episodes. In Fig. 4(a), the retrieval cue consists of incomplete/complete and erroneous/error-free events of the fourth episode E_4 such that the match value m_4 for E_4 from F_2 to F_3^{epi} is greater than or equal to ρ_{epi}. On first activation of E_4, the memory strength s_{E_4} is less than the semantic memory threshold s_t^{sem}. Hence, E_4 is retrieved from F_3^{epi} and F_3^{sem} is empty. In Fig. 4(b), the retrieval cue consists of incomplete/complete and erroneous/error-free events of the fourth episode E_4 such that the match value m_4 for E_4 from F_2 to F_3^{epi} is greater than or equal to ρ_{epi}. On the second activation of E_4, the memory strength s_{E_4} becomes greater than the semantic memory threshold s_t^{sem}. Hence, E_4 is copied to F_3^{sem} and is retrieved from F_3^{epi}.

In Fig. 4(c), the retrieval cue contains incomplete/complete and erroneous/error-free events of the fourth episode E_4 such that the match value m_4 for E_4 from F_2 to F_3^{epi} and from F_2 to F_3^{sem} is greater than or equal to ρ_{epi} and ρ_{sem}, respectively. E_4 is in both F_3^{epi} and F_3^{sem} and can be retrieved from either F_3^{epi} or F_3^{sem}. Finally, in Fig. 4(d), the retrieval cue contains incomplete and erroneous events of the fourth episode E_4 such that the match value m_4 for E_4 from F_2 to F_3^{epi} and from F_2 to F_3^{sem} is less than ρ_{epi} and greater than or equal to ρ_{sem}, respectively. E_4 is in both F_3^{epi} and F_3^{sem} but can only be retrieved from F_3^{sem} because of high error rate in the retrieval cue and low flexibility of F_3^{epi}. Hence, E_4 is retrieved from F_3^{sem}. A pseudocode highlighting retrieval and semantic-like memory formation procedure are presented in Algorithm 2.

Algorithm 2 pDM-ART Retrieval and Memory Consolidation

1: **BEGIN**
2: **FOR** every incoming event in retrieval cue
3: Select a resonant node J in F_2
4: Let node activation y_J be 1 or any predefined maximum value
5: **FOR** every previously selected node j in F_2
6: Let its activation be $y_j^{new} = y_j^{old}(1-\tau)$ or 0 if $y_j^{old} \leq 0$
7: Based on the activation vector y formed in F_2:
8: Select a resonant node R in $F_3^{epi} \cup F_3^{sem}$
9: **if** R is found in F_3^{epi} **then**
10:     Increase $s_{E_R}(t)$ for R by
11:     $s_{E_R}(t) = s_{E_R}(t-1) + (1 - s_{E_R}(t-1))r_s$
12: **end if**
13: **for** every other node **do**
14:     Decrease $s_{E_R}(t)$ by
15:     $s_{E_R}(t) = s_{E_R}(t-1)(1-\delta_s)$
16: **end for**
17: **if** s_{E_R} for R is $\geq s_t^{sem}$ and R is not in F_3^{sem} **then**
18:     Copy R to semantic memory component F_3^{sem}
19:     Learn the associated weight vector $\mathbf{w}_R^{(sem)} = \mathbf{w}_R^{(epi)}$
20: **end if**
21: Readout weights from F_3^{epi} and F_2 or F_3^{sem} and F_2
22: **if** learning is allowed **then**
23:     **if** resonance occurred in F_3^{epi} **then**
24:         Update weights in F_2 and F_3^{epi} using β_{e_j} and β_{E_r}, respectively
25:     **end if**
26:     **if** resonance occurred in F_3^{sem} **then**
27:         Update weights in F_2 and F_3^{sem} using β_{e_j} and β_{sem}, respectively
28:     **end if**
29:     **if** resonance occurred in F_3^{epi} and F_3^{sem} **then**
30:         Update weights in F_2, F_3^{epi} and F_3^{sem} using β_{e_j}, β_{E_r} and β_{sem}, respectively
31:     **end if**
32: **end if**
33: Exit Loop
34: **END**

Note that at resonance, the memory strengths of nodes in F_3^{sem} do not change. Only those memories that are in F_3^{epi} get their memory strengths increased or decreased. Also, note that the decision to update weights in steps 24, 27, and 30 during the retrieval process lies with the user (step 22). When learning is not allowed during retrieval, the weights of learned memories remain unchanged. Hence, memories remain stable unless the user wants the memories in F_3^{epi} and F_3^{sem} to generalize based on incoming activity pattern. Due to higher learning rate in F_3^{epi}, weights change much quicker than in F_3^{sem}. On the other hand, F_3^{sem} is prone to higher level of generalization because of the low vigilance parameter ρ_{sem} that leads to resonance, and hence, weights update in many more cases than in F_3^{epi}.

TABLE I
COMPARISON OF SPACE AND TIME COMPLEXITY

	pDM-ART	EM-ART
Space complexity (nodes)	$O(e+E)$	$O(e+E)$
Space complexity (weights)	$O(ea+Ee)$	$O(ea+Ee)$
Time complexity (Encoding)	$O(mea+Ee^2)$	$O(mea+Ee^2)$
Time complexity (Retrieving)	$O(mea+Ee^2)$	$O(mea+Ee^2)$

VI. COMPLEXITY ANALYSIS

In this section, we analyze the space and time complexity of pDM-ART for encoding and retrieving events and episodes. Consider the task of encoding E episodes with e unique events. For each event, we suppose there is a fixed set of a attributes associated with it. In addition to that, among E episodes, there is an average of m events and a maximum of M events. Also, in F_3^{sem}, there can be a maximum of E episodes and a minimum 0 episodes in the case when the semantic component is not yet formed. The space and time complexity is shown in Table I for both EM-ART and pDM-ART. We see that that embedding a user preference and a consolidation-like procedure does not affect the complexity of the EM-ART, the model from which pDM-ART is adapted.

A. Space Complexity

Space complexity refers to the amount of space that is needed by an algorithm or a memory model in terms of the amount of input. As discussed earlier, for encoding e number of events, pDM-ART requires e number of nodes in F_2 layer. Each event has a attributes and because the event, as a multimodal pattern, is stored in the a weighted connections to the F_1 layer, we will have a total of ea connections between the F_1 and F_2 layers keeping in mind that we did not employ complement coding. The number of nodes that are required to store E number of episodes is E and each F_3^{epi} node is connected to all the e nodes in F_2. Hence, the number of connections between F_2 and F_3^{epi} is Ee. After the semantic-like memory component is formed, the maximum number of nodes that can be in F_3^{sem} is E, and hence the maximum number of connections from F_2 to F_3^{sem} is Ee. On the other hand, when no episodes have undergone consolidation yet, there are 0 or no nodes in F_3^{sem}. Therefore, the total number of nodes required in pDM-ART is minimum $e+E$ and maximum $e+2E$. And similarly, the number of weights required is minimum $ea + Ee$ and maximum $ea + 2Ee$. The vigilance parameters ρ_e, ρ_{epi} and ρ_{sem} can be increased or decreased correspondingly to an increase or decrease in the number of nodes and weights.

B. Time Complexity

Time complexity is basically a function describing the amount of time an algorithm takes in terms of the amount of input to an algorithm/model. In pDM-ART, a total of ea comparisons are required during the resonance search operation from F_1 to F_2. If there is an average of m events in each episode, pDM-ART takes mea processing steps to produce a series of activations in F_2. If there are E episodes in F_3^{epi}, it will require Ee^2 amount of processing time to compare the activation pattern in F_2 with E number of nodes in F_3^{epi}. Therefore, the time associated with encoding of an episode is given by $mea + Ee^2$. On the other hand, the time required to retrieve an episode is minimum $mea + Ee^2$ if there are no nodes in F_3^{sem} and maximum $mea + 2Ee^2$ if there are E number of nodes in F_3^{sem}.

VII. Results and Comparisons

One of the key parameters for EM-ART model is the vigilance parameter, which defines the matching threshold for a template. Generally, EM-ART gives a higher retrieval accuracy when the vigilance criterion is lowered [38]. The higher the vigilance criterion, the more strictly the patterns should match for resonance. However, the high retrieval accuracy at lower vigilance values for the types of cues in [38], including partial cues from the beginning, partial cues from the end, partial cues from arbitrary locations, noisy cues in terms of event representation, and noisy cues in terms of event sequence, comes with a compromise of the distinct experiences that the model can learn. The amount of partiality and noise in the cues is referred to as rate of error in this paper. In a simulation analysis (see Fig. 5, in which cues used for these results are the same as the ones used in Sections VII-C and VII-D) that we performed using a set of ten distinct experiences described in Section VII, it is observed that while the retrieval percentage is generally higher for cases when ρ_{epi} is lower, the number of distinct experiences learned correctly if the experiences are similar yet distinct enough is lesser than when the ρ_{epi} is higher. The first and the last scenario are an example of such a case. In Fig. 5, apart from the cues that are partial from the beginning, in all other types of retrieval cues, the percentage of successful retrieval of learned episodes is higher at lower vigilance values, while the number of distinct episodes learned is higher when ρ_{epi} is higher. One of the contributions of our adaptation to EM-ART, by developing two routes for retrieval, is to try to overcome this compromise.

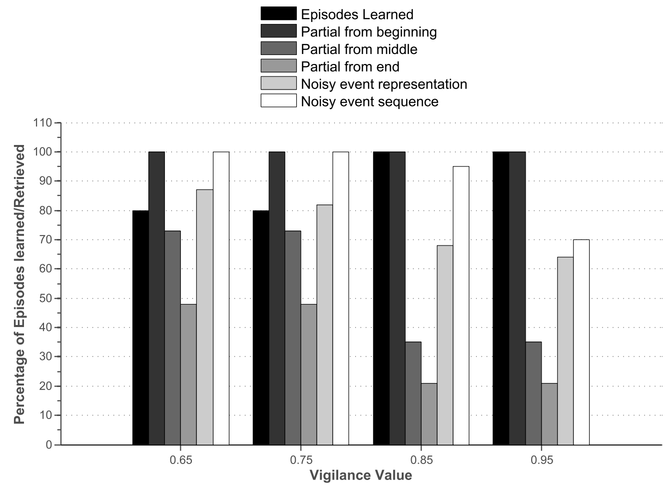


Fig. 5. Percentage of learned episodes and successful retrieval of learned episodes by EM-ART at various values of ρ_{epi}.

In this section, we evaluate the performance of our model and compare it with EM-ART. The comparison is done to test whether adding an alternate route (F_3^{sem}) to EM-ART by memory consolidation mechanism improves the retrieval accuracy of episodic memories with increasingly degrading cues compared with when there is only one route as in EM-ART. EM-ART outperforms other models in [38], while having the performance similar to LTM [27]; hence, EM-ART is chosen for benchmarking. For evaluation purpose, we used a test bed that consists of ten distinct experiences/tasks, which include *Water the flowers and read a book after*, *Take out a book from a drawer*, *Pour the contents of a bottle*, *Sort the toys*, *Toast a slice of bread*, *Take out a bottle from the fridge*, *Put glass from a shelf on a tray*, *Heat a meal in microwave*, *Clean the room with a broom*, and *Read a book to a friend*. All of these tasks consist of sequences of events; for example, the task *Water the flowers and read a book after* consists of a sequence of 11 events {*Move to a drawer, Open the drawer, Grasp a watering pot, Move with the watering pot to the flowers, Tilt the watering pot to the flowers, Move with the watering pot to the table, Put the watering pot on the table, Move with the book to a chair, Sit on the chair with the book, Read the book*}. Similarly, sequences of events from a set of around 40 more events constitute the remaining nine tasks. Details of these are not shown due to space constraints. Some of these simulation scenarios are similar to the ones used in [40] and [46]. The three terms, tasks, episodes, and experiences, would be used interchangeably in this section. Scenario 1 is a combination of two tasks in order to have a longer sequence of events and to have two similar yet distinct experiences (Scenarios 1 and 10). For learning of these scenarios, two inputs are used to represent the event: an action and an object. There are a total of 13 actions {*Grasp, Move, Lean, Putdown, Open, Close, Pour, Pushdown, Read, Sit, Putin, Clean, Set*} and 23 objects {*Wateringpot, Flower, Table, Drawer, Book, Bottle, Bowl, Toy, Box, Bread, Toaster, Chair, Cup, Fridge, FridgeHandle, Tray, Shelf, Glass, Food, Microwave, Broom, Room, Friend*} that are employed for generating the scenarios. For pDM-ART, along with the action and the object, an importance factor I is associated with each event to specify user preference. The end result of applying this model to a robot can be briefly summarized in the following words. With pDM-ART, not only will a robot with pDM-ART be able to learn and retrieve an experience of, for example, *Toasting a bread*, but also it will be able to retrieve the experience from cues with higher rate of error as that experience is consolidated by the repetition of *Toasting a bread* and/or associating a higher I with it if the user wants to further speed up the consolidation timing for the task of *Toasting a bread*. A practical scenario is discussed in Section VIII.

A. Setting of Importance Parameter

The importance parameter I has to be set for each event at the time of encoding. Then, the importance parameter for each episode is automatically set by (8). The importance parameter can be based on user feedback, artificial emotions of the robot, any one of the two or both, or even any other factor that a user would like the memories to be adapted with. In our simulation experiments and experiments using Mybot in Section VIII, the value of I is a quantification of how important a particular event is in the view of the user, so I is defined based on a user feedback.

For practical experiments, user feedback can be recorded in various ways. For example, one way of doing this would be a robot performing a task for the first time based on a state machine while the user gives verbal feedback or feedback via facial expressions. Another method may be that the user demonstrating the task for learning and giving feedback along with each step. This would be based on what the user thinks is more important and what the user would like the robot to learn better/faster than certain other tasks. This feedback can be verbal. These sensory (verbal/facial expressions) inputs can then be converted into numerical values of I by comparing against a predefined feedback function *feedback*(). The feedback function can be tuned by any user based on their preferences. To design a robust feedback function, we may need a classifier that can classify the verbal input or facial expressions after it has been trained or an LSTM classifier [28] that can identify if the feedback was positive or negative. We believe this is a whole new area that requires full concentration and since this paper does not focus on the modeling aspect of I, we would like to include this as possible future work. A probable method for assigning I to each event is provided in Algorithm 3 without going into the details of modeling of the feedback function. In Sections VII and VIII, the feedback was given manually by the user during the learning phase.

Algorithm 3 Generation of Importance Parameter for Each Event

```
Define feedbackfunction()
Begin
while LEARNING do
    for each EVENT e_j do
        Get feedback f_{e_j} from user
        Calculate I_{e_j} = feedbackfunction(f_{e_j})
    end for
end while
END
```

For evaluating pDM-ART, once the aforementioned scenarios as ten distinct episodes had been learned, we tested its performance with various types of cues. 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 set of cues, the experiment was performed for ten trials with the same set of cues in each trial. Also, each experiment was performed in three different cases with a varying importance parameter. The first two cases consist of a fixed I value (0.5 and 0.8) for each event and the last case assigns I values randomly from 0.5 to 1 to all events with a higher value of I indicating a higher importance. The objective was to analyze the consolidation trend and the improvement in retrieval accuracy with each trial whenever an episode (episodes) is consolidated. The retrieval accuracy is defined by the number of times an episode is correctly retrieved over the total number of cues in one trial. Overall, the results show that the model was able to improve the retrieval accuracy for the learned experiences as the episodes were consolidated. Consolidation of episodes was also higher and faster when I was higher, and for each case of I, percentage of consolidation was higher as the number of trials increases, which was due to the increase in frequency of recall of a certain episode. Also, the retrieval accuracy for pDM-ART was always equal to or higher than EM-ART across all experiments.

B. Generation of Cues for Each Experiment

The cues for each type of error (first five experiments) were generated as shown in Algorithm 4. We define the trials to be continuous, which means the values of memory strengths s_{e_j} at the start of trial $n+1$ are the same as the memory strength values at the end of trial n. The parameters for pDM-ART and EM-ART were, respectively, initialized as follows.

1) $\rho_e = 0.9, \rho_{\text{epi}} = 0.95, \rho_{\text{sem}} = 0.65, \beta_{\min} = \gamma_{\min} = s_{\min} = 0.5, \delta_s = 0.0001, r_s = 0.5$, and $s_t^{\text{sem}} = 0.95$
2) $\rho_e = 0.9, \rho_{\text{epi}} = 0.95, \beta_{e_j} = 0.8$ (for all channels from layer F_1 to F_2), $\beta_{E_r} = 0.8, \delta_s = 0.0001$, and $r_s = 0.5$.

We also tested the performance for all of the experiments using $\rho_{\text{sem}} = 0.65$, 0.70, and 0.75. Due to similarity in the results and the large number of results, we present only the performance of the model with ρ_{sem}= 0.65. Also, we tested the model in both cases, i.e., when learning is allowed during retrieval and when it is not. In the case when learning

Algorithm 4 Generation of Cues for Each Trial

Error rate r and $r_{max} \in [0, 100]$
Maximum trial number $n \in [0, 15]$
$r = 0$
Begin
for i= 1 to n **do**
    while $r \leq r_{max}$ **do**
        for j = 1 to number of episodes learned **do**
            Introduce error r
        end for
        Increment error r
    end while
end for
END

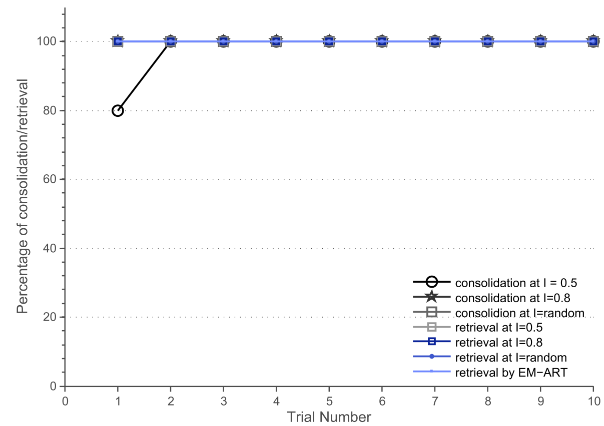


Fig. 6. Testing with partial cues from the beginning. Percentage of consolidated episodes and correctly retrieved episodes by pDM-ART for three cases of I ($I = 0.5$ for all events, $I = 0.8$ for all events, and I = randomly set for each event, whereas the values range from 0.5 to 1) for ten continuous trials. The retrieval accuracy for EM-ART is also shown.

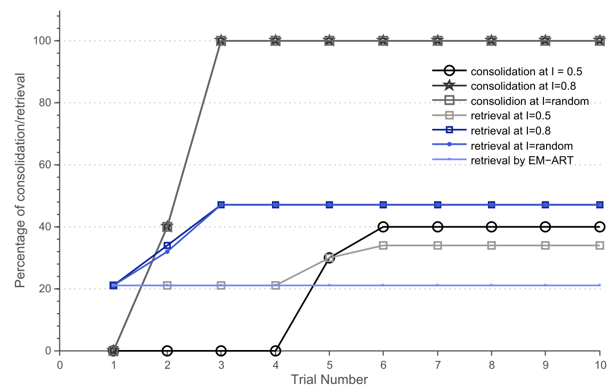


Fig. 7. Testing with partial cues from the end. Percentage of consolidated episodes and correctly retrieved episodes by pDM-ART for three cases of I for ten continuous trials. The retrieval accuracy for EM-ART is also shown.

is allowed, the retrieval rates for Sections VII-A2 and VII-B1 are observed to be a little lower, but otherwise the retrieval rates are similar in both cases with the test bed used in this paper. The lower retrieval rate in the case when weights are updated during retrieval is due to the higher level of generalization disabling F_3^{sem} in retrieving some of the episodic memories when the cues are almost complete or less noisy but still partial or noisy enough to avoid resonance in F_3^{epi}. The retrieval rates in either case highly depend on the design of the cues that are applied to retrieve memories. Due to space constraints, we have included only results for the simpler case when learning was not allowed.

The general guideline for choosing $\beta_{\min}$, $\gamma_{\min}$ and $s_{\min}$ is to choose values, which may give a suitable rate (according to the user), the lowest or highest possible learning rate β_{e_j}, contribution factor γ_{e_j}, and memory strengths $s_{e_j}^{\text{init}}$ for events. For example, in our case, we used $\beta_{\min} = \gamma_{\min} = 0.5$, which gives β_{e_j} and γ_{e_j} their possible maximum and minimum values as 1 and 0.25, respectively. The same is done for $s_{\min}$. The limits of $\beta_{\min}$, $\gamma_{\min}$, and $s_{\min}$ control the limits of β_{e_j}, γ_{e_j}, and $s_{e_j}^{\text{init}}$, respectively. For values less than 0.4 for $\beta_{\min}$, $\gamma_{\min}$, and $s_{\min}$, the values for β_{e_j}, γ_{e_j}, and $s_{e_j}^{\text{init}}$ can become negative for $I_{e_j} \in [0, 1]$. Similarly, the limits of $\beta_{\min}$, $\gamma_{\min}$, and $s_{\min}$ also control the limits of β_{E_r}, γ_{E_r}, and $s_{E_r}^{\text{init}}$, respectively.

C. Retrieval With Partial Cues

Three kinds of partial cues were tested.

1) Retrieval With Partial Cues From the Beginning: In the first experiment, we used a total of 10 trials and each trial consisted of the same set of 46 cues in which there is at least one instance of a complete cue for each of the 10 episodes. The remaining cues are partial cues from the beginning, in the increasing order of error, with lengths up to one-fourth of the original length. Fig. 6 illustrates consolidation and retrieval for pDM-ART for the three cases of I. The retrieval curve for EM-ART is also shown. We observe that in this experiment, the retrieval rate is 100% for all trials and for all three cases of importance parameter. Moreover, the retrieval rate for EM-ART is also 100%. It can be seen that the consolidation of all the ten episodes was achieved as early as in trial 1 except for the case when I=0.5. This is because at a lower value of I, a higher number of retrievals are required to increase memory strengths beyond the semantic-like memory threshold value s_t^{sem}.

2) Retrieval With Partial Cues From the End: In this retrieval test, a total of 10 trials were used with each trial consisting of the same set of 46 cues, which, apart from at least one instance of a complete cue, were partial cues from the end with lengths up to one-fourth of the original length. Fig. 7 shows the performance of pDM-ART in all three cases of I. We see that the consolidation rate varies greatly for the three cases. When I= 0.5, only 40% of episodes are consolidated even as late as trial number 10. A lower value of I sets low initial memory strengths. Also, the memory strength associated with each episode decreases by an amount given by δ_s every time that episode is not recalled. This means that for a longer set of cues, the memory strength values will be lower at the end of each trial than for a set of shorter cues. We also see that the retrieval accuracy increases as the number of consolidated episodes increases. The retrieval rate for EM-ART remains the same in all the ten trials. It is because EM-ART in [38] does not have a mechanism to cater for the recurrent or significant experiences.

3) Retrieval With Partial Cues From the Center of Episodes: Just like the last two experiments, we used 10 trials with

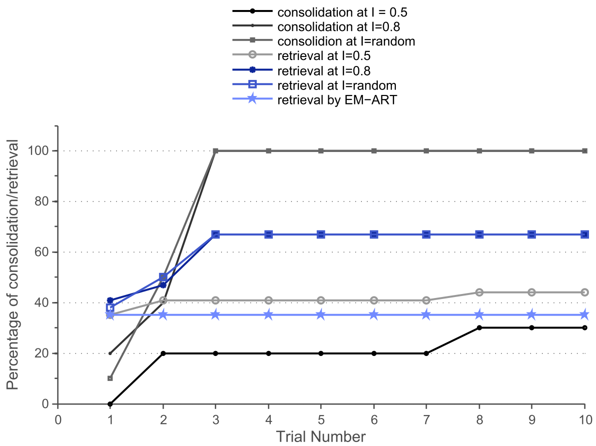


Fig. 8. Testing with partial cues from the center of episodes. Percentage of consolidated episodes and correctly retrieved episodes by pDM-ART for three cases of I for ten continuous trials. The retrieval accuracy for EM-ART is also shown.

36 cues in each, which, apart from one complete instance of each episode, consists of partial cues from the center of those episodes with lengths up to one-fourth of the original length. The results for consolidation and retrieval for the three cases of I can be seen in Fig. 8. As expected, we observe three different consolidation patterns for each case of I with faster consolidation for all episodes in the case of I being higher. Following the trend as in previous tests, the retrieval rate also increases whenever the percentage of consolidated episodes increases.

D. Noisy Cues

The model is tested with two kinds of noisy cues. One type of noise was generated by introducing an error in the events attributes and the second was generated by introducing error in the sequence of the events in one particular episode.

1) Retrieval With Noisy Cues in Terms of Event Representation: For testing the performance against noisy cues with the first type of error, we used a set of 50 cues in each of the 10 trials. This set of cues consists of at least one instance of a noise-free episode and the remaining are cues with an increase of error from 10% to 40% in terms of event attributes. This kind of noise was generated as shown in Algorithm 5.

The performances of pDM-ART and EM-ART are shown in Fig. 9. We observe the same trend in $I = 0.5$, where the consolidation rate is slower than for when $I = 0.8$. Also, we note that for each case of I, the consolidation rate is much faster for noisy cues in terms of event representation than for partial cues from the end or the middle. This is because the retrieval rates are lower for the latter in each trial and the recall frequency of an episode has a direct effect on increasing the memory strength, which in turn leads to consolidation. As expected, the performance of EM-ART remains constant along all trials.

2) Retrieval With Noisy Cues in Terms of Event Sequence: For the second type of noise, a set of 90 cues was used in each trial. The set consists of cues with at least one instance of noise-free cue and the rest of the cues are scrambled cues in terms of the sequence of events in one particular episode. The error introduced is in an increasing order from 10% to 80%. Algorithm 6 illustrates how this type of error is generated.

Algorithm 5 Noise Generation in Terms of Event Representation

Error rate $r \in [0, 100]$
BEGIN
for each EPISODE in original data set **do**
  for each EVENT in an episode **do**
    for each attribute a in each event **do**
      Generate a random number x between 1 to 100
      if $x \leq r$ **then**
        attribute $\tilde{a} = 1 - a$
      end if
    end for
  end for
end for
END

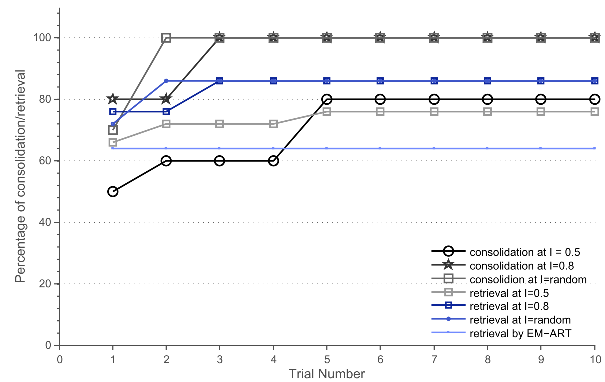


Fig. 9. Testing with noisy cues in terms of event representation. Percentage of consolidated episodes and correctly retrieved episodes by pDM-ART for three cases of I for ten continuous trials. The retrieval accuracy for EM-ART is also shown.

In this experiment (Fig. 10), generally a higher percentage of consolidation and retrieval was observed across all three cases of I. A higher retrieval accuracy in the first trial leads to 100% consolidation as early as in trial 1 except in the case when $I = 0.5$. This is because the memory strength levels for some episodes are not able to cross the threshold value s_t^{sem} even after being retrieved multiple times in trial 1 and also because of the longer set of cues in each trial. Additionally, in all three cases of I, we see that the performance remains the same throughout the trials after trial 1. This is because maximum consolidation is achieved as early as in the first trial, and due to that, the best possible performance is also achieved accordingly right after the first trial. Hence, we see no improvement after the first trial in all three cases. The performance of EM-ART is constant as expected.

E. Performance Test With Cues With All Types of Errors

After testing the model for five different types of cues separately, we observed the consolidation and retrieval performances of pDM-ART with all types of cues in a single data set. The different types of cues were mixed to give a set

Algorithm 6 Noise Generation in Terms of Event Sequence

Error rate $r \in [0, 100]$
BEGIN
for each EPISODE S in original data set **do**
  index = random number from 1 to $[S.length * r/100]$
  while $S_{temp}.length \leq [S.length * r/100]$ **do**
    $S_{temp}.e_i = S.e_{index+i}$
    $i \leftarrow i + 1$
  end while
  $S_{shuffle} = permutate\_randomly(S_{temp})$
  for $i = 0$ to $[S.length * r/100] + 1$ **do**
    $S.e_{index+i} = S_{shuffle}.e_i$
  end for
end for
END

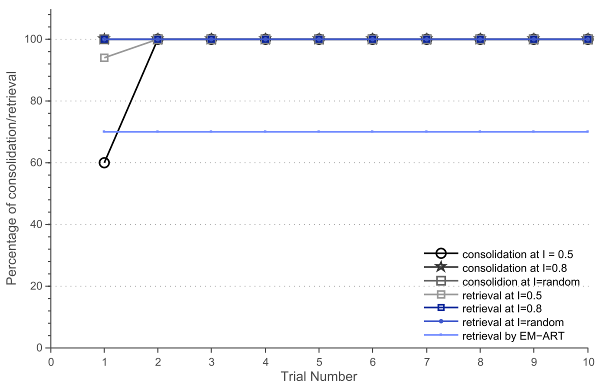


Fig. 10. Testing with noisy cues in terms of event sequence. Percentage of consolidated episodes and correctly retrieved episodes by pDM-ART for three cases of I for ten continuous trials. The retrieval accuracy for EM-ART is also shown.

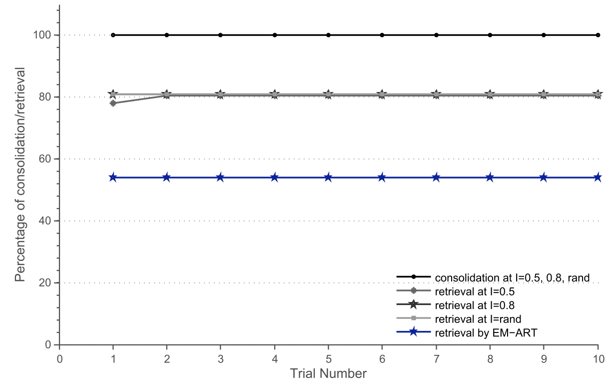


Fig. 11. Performance test with cues with all types of errors. Percentage of consolidated episodes and correctly retrieved episodes by pDM-ART for three cases of I for ten continuous trials. The retrieval accuracy for EM-ART is also shown.

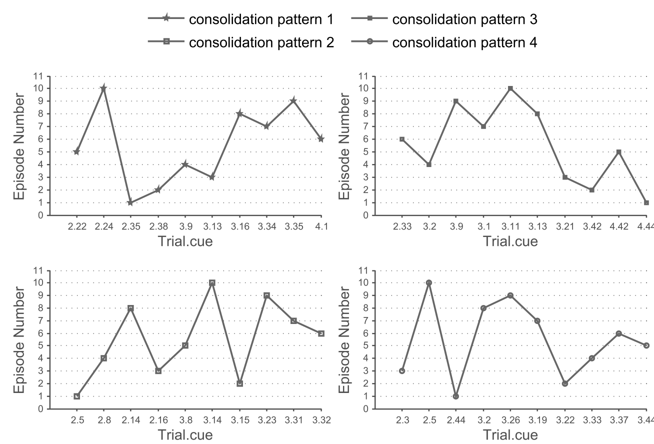


Fig. 12. Illustration of four different patterns of episode consolidation demonstrating the effect of the randomness of the cues. In the x-axis, the first number is the trial number, while the fractional part is the cue number in that trial.

of 226 cues for each of the ten trials. Results can be observed for both EM-ART and pDM-ART in Fig. 11. In all three cases of I, we again observe that the performance remains the same throughout the trials after trial 1. The reasoning is the same as for the previous case.

F. Effect of Randomness of Cues on the Consolidation Pattern

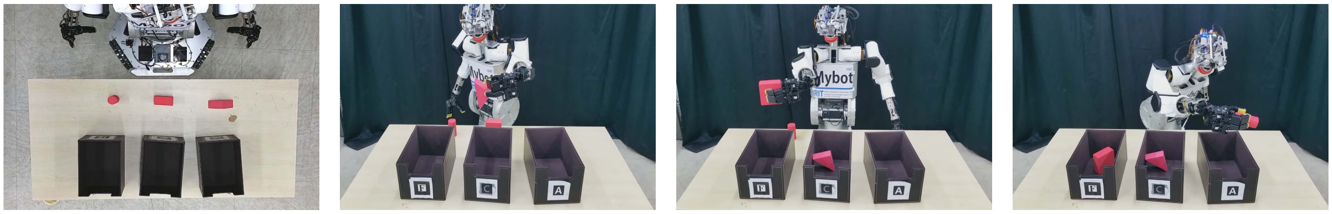
The objective of this test was to observe the effect of randomness in the order of the cues on the pattern of episode consolidation. In the first five tests, the order of cues was in the order of increasing error. In this experiment, we demonstrated the effect on the consolidation pattern of episodes if the cues were not ordered (from zero to maximum error $r_{\max}$) but were placed randomly. We repeated the test five times for the set of cues used in Section VII-A2 randomly ordered. Fig. 12 illustrates four different consolidation patterns that were produced as a result of the randomness of cues.

G. Unique Episode of Importance

If a unique episode of significance is learned with the maximum value for the importance parameter $I_{\max} = 1$, then it could be consolidated ($s_{E_r}(t) \geq s_t^{\text{sem}}$) after one successful recall. Once consolidated, it can be retrieved at higher levels of errors in partial/noisy cue. On the other hand, if a unique episode of insignificance is learned, e.g., at an average value $I = 0.5$, then as seen by various results above, it will require at least five successful retrievals from episodic memory before it can be consolidated. Since it is a unique episode, there is a high chance that it may be forgotten before having a chance of five successive recalls to be consolidated. In effect, this system of preference based episodic memory with online consolidation process is able to distinguish between episodes of importance and insignificance.

VIII. Experiments on Mybot

We tested a simple scenario with Mybot, a robot developed in the Robot Intelligence Technology (RIT) Laboratory at KAIST. It makes use of Odroid XU board, Ubuntu 14.04 and ROS. In this scenario, it was expected to act as a service robot that was taught five tasks (episodes) including *Arrange the Red Circular Toy in Box A*, *Arrange the Red Square Toy in Box F*, *Arrange the Red Rectangular Toy in Box C*, *Bring Cola from Counter to Table and pour it in a Cup*, and *Bring Coffee from Counter to Table and pour it in a Mug*. The user had no particular preference for any task except for the fourth task. While the user did not mind that the other four tasks can



(a) (b) (c) (d)

Fig. 13. (a)–(d) Mybot performing three tasks of arranging RedCircularToy, RedSquareToy, and RedTriangularToy in BoxA, BoxF, and BoxC, respectively.

(a) (b) (c) (d) (e)

Fig. 14. (a)–(e) Mybot performing the task of bringing Cola from the counter to the table and pouring it in a cup.

be consolidated and hence learned better by Mybot based on only the frequency of retrieval as the time goes by, the user wanted Mybot to consolidate the fourth task faster, and hence I_{E_4} was set higher comparatively.

The experimental conditions were set similar to Section VII-A3 except that the set of cues were different. Importance I was set manually by the user for the events considered significant by the user, while for all other events I was assumed to be 0.6. In the first trial, all the tasks were retrieved with three-quarter length retrieval cues for tasks with longer sequences (fourth and fifth tasks) and half-length retrieval cues for tasks with shorter sequences. However, in the fourth trial, the fourth task was retrieved even with half length of the retrieval cue, but the other tasks could still only be retrieved by three-quarter length long retrieval cues in the case of the fifth task and half-length cues for the other tasks. This is because even though all the tasks had the same frequency of retrieval, due to higher significance associated by the user, the fourth task was consolidated earlier in the fourth trial, while the remaining tasks were consolidated later. Hence, after consolidation, due to the second route with lower ρ_{sem}, a representation of that task in F_3^{sem} facilitated in the retrieval of the fourth task relatively easily even with a cue of (1/2) length. Hence, pDM-ART allowed a service robot to distinguish significant and recurrent tasks (episodes) from other equally recurrent but less significant tasks. Figs. 13 and 14 demonstrate the first three tasks and the fourth task, respectively. The fifth task (similar to the fourth task) is not shown due to space constraints. A clip from the experiment is available at: http://rit.kaist.ac.kr/home/pDM-ART.

IX. Conclusion

This paper proposed a user preference-based dual-memory model, which, over a period of time, forms a semantic-like memory component alongside an episodic component based on: 1) a user-defined importance factor at the time of encoding and 2) recall frequency. These consolidated episodes then assist in retrieving the experiences learned by the model. Taking advantage of the flexible design of the semantic-like memory component, pDM-ART becomes increasingly robust to erroneous cues with two routes for retrieval of experiences. This dual-memory model promises to be an efficient memory model for service robots in HRI, task intelligence, and other cognition problems, which require a mechanism to distinguish between significant and insignificant and recurrent and sporadic experiences, and to adapt learning based on an external feedback.

It should be noted that the objective of this memory model can be achieved by keeping a single episodic memory component and instead introducing dynamic vigilance rates, which are influenced by the importance parameter and the recall frequency. However, we chose to reach the goal by dedicating an entire new semantic-like memory component, which does not consist of episodes learned by a single experience but only those that are recurrent and significant to the user. As the consolidated nodes are activated relatively easily by cues with higher rates of error (but still have enough similarity to achieve an average vigilance criterion; $\rho_{\text{sem}} = 0.65$ in our case), over a period of time as the weights are updated (with a lower learning rate β_{sem} and when learning is allowed during retrieval), the isolated events fade from the episodes stored in F_3^{sem} and only the frequent events remain in the episode. Thus, as the episode is experienced repeatedly, a gist of the more frequent events in that episode remains in F_3^{sem}. These frequent events can then represent a *concept* of doing a particular task.

The semantic-like memory described in this paper is limited and differs from the formal definition of semantic memory since it is only constructed through the consolidation of experiences (episodes in episodic memory) to formulate conceptual representations for a particular task and does not currently include symbol grounding or any associations between symbol grounding and the high-level concepts. Also, this semantic-like memory is related to episodic memory used in this paper as the consolidated episodes in semantic-like memory still very much represent a spatiotemporal sequence, which is, however, a sequence that is prone to slow degradation over time to represent only the most frequent of the events in a sequence. This along with its ability to retrieve relatively easily due to the low vigilance criterion in F_3^{sem} and to be more stable comparatively due to the low learning rate in F_3^{sem} is what makes it relatable to high-level concepts in semantic memory. For future work, we intend to work on the limitations of the semantic-like memory by tackling the symbol grounding problem and integrating a map of semantically related objects and behaviors with F_3^{sem}. This would truly make use of the semantic-like memory component proposed in this paper by forming associations between high-level concepts in F_3^{sem} and among low-level grounded representations and low-level grounded representations, expanding the general knowledge of the system about the world.

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