Integrated Adaptive Resonance Theory Neural Model for Episodic Memory with Task Memory for Task Performance of Robots

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***Abstract*—Episodic memory is the memory of personal experiences as episodes with subjective time. Task memory is defined as a memory for storing the knowledge of sequential procedures to perform tasks. Rather than encoding and retrieving such a temporal sequence of events or procedures, respectively, it is more efficient to implement both memories into a single memory model together. For this purpose, this paper proposes an integrated adaptive resonance theory (I-ART) neural model for episodic memory with task memory. The performance of the proposed episodic memory model is confirmed through comparison study with the other methods. And the proposed task memory is applied to perform tasks by Mybot-KSR2, developed in RIT Lab., KAIST.**

I. Introduction

Episodic memory refers to the memory of personal experiences as episodes with subjective time. This type of memory stores temporal events in a sequential form. Episodic memory plays important roles in the mental activities tied strongly to time information such as remembering, thinking about the past, expecting, planning, and thinking about the future [1]. In research on computational intelligence, the crux is on how to mimic and implement episodic memory, including subjective times and places. Specifically, designing such a memory model for robots to perform tasks is essential, as the previous works without implementing episodic memory only focused on learning the specific action at a time [2]-[6]. Episodic memory based schemes were applied to anticipatory robot control and robotic cognitive behavior control other than task performance of robots [7], [8].

Various research has been performed to implement a single spatio-temporal memory system modeling long-term memory including episodic memory. A long short-term memory (LSTM) system introduces a memory cell in a recurrent neural network (RNN), which is among the most powerful methods for developing sequential memory, enabling the RNN to learn sequences with a long time lag [9]. A long-term memory (LTM) is the hierarchical architecture inspired by human visual cortex, and a hierarchical temporal memory (HTM) with memory-prediction theory is based on an interpretation of the neocortex [10], [11]. An episodic memory adaptive resonance theory (EM-ART) stands out owing to its ability to store the spatio-temporal relationships between various events and then to retrieve them with higher tolerance towards noise compared with previous models of spatio-temporal memory [12]. This network was built by hierarchically combining two multi-channel fusion ART networks [13], [14].

Humans learn the procedures involve in performing a task from the past experiences. To employ this feature for robots, we define task memory as a memory for storing sequential procedures to perform tasks. Both memories are obtained from the past experiences, and task memory, encoded as a sequence of procedures, has similar functions of episodic memory in terms of memorizing temporal patterns. Rather than representing the episodic memory and task memory, respectively, it is more efficient to represent both episodic memory and task memory in a single memory model by sharing the similar functions for both of encoding and retrieval. By extracting the similar functions in episodic memory and procedural memory, an integrated memory model was introduced, where the joint perceptuomotor mapping was employed for perceptual episodic memories and motoric procedural memories [15]. However, this memory model mainly focused on a way of mapping perception with motor commands for execution rather than encoding retrieving the temporal patterns, such as a sequence of procedures.

In this paper, we propose an integrated adaptive resonance theory (I-ART) neural model for episodic memory with task memory, which enables robots to infer the available task to be performed and retrieve the sequence of procedures. In I-ART, an episode is represented as a sequence of events or tasks. Both of an event and a task are handled identically in terms of episodic memory. The only difference between them is that a task itself has a sub-sequence, a sequence of procedures. To encode and retrieve a sequence of procedures to and from a task, task memory is introduced. The task memory as well as episodic memory is represented as EM-ART. The task memory exists within episodic memory with sharing some functions. Additionally, in I-ART, input channels are connected from the input field directly to the event/task field. The information from these input channels can be utilized as a cue for retrieval. The proposed I-ART is compared with the other methods for

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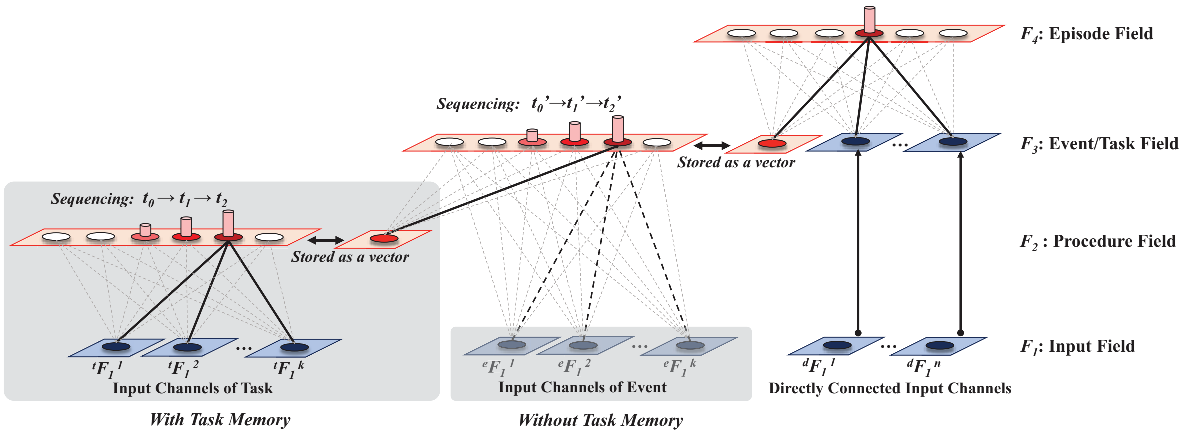

Fig. 1. Architecture of the proposed I-ART network.

the performance. The effectiveness of the proposed I-ART is demonstrated through computer simulations and experiments showing that a robot can store both episodes and a sequence of procedures together to the I-ART network and retrieve them separately from the network with different procedure-related cues for task memory, and task-related cues, a subjective time, and/or a place for episodic memory.

The rest of this paper is organized as follows. Section II presents the architecture of the proposed I-ART. Sections III and IV describe the algorithms and methods used to encode and retrieve episodic memory with task memory, respectively. Sections V and VI present the comparison study with the other methods, and simulation and experimental results, respectively. Finally, concluding remarks follow in Section VII.

II. Proposed I-ART

The proposed I-ART memory model consists of four layers of memory fields: the input field, procedure field, event/task field, and episode field, as shown in Fig. 1. The input field gets information related to a given situation, such as actions, objects, time, place, etc. In I-ART, certain input channels, ${}^dF_1^i$s are connected from the input field directly to the event/task field, and the information from the input channels can be utilized as a cue for retrieval. Specifically, I-ART has a subjective time and place as inputs which are directly connected from the input field to the event/task field. When such an input is used for retrieval in I-ART, due to the separately connecting channel which has an independent influence on the reproduction of memory, the corresponding memory can be retrieved without referring to the other input information. The changes of such inputs are recognized with a lower frequency than the other inputs. In the sense that the time scales of some inputs become longer in the higher field, our model is similar to a multiple timescales recurrent neural network (MTRNN) [16].

Based on the activation of channels in the input field, a category node in the procedure field is selected and activated [13], [14]. The activation of an incoming procedure can be learned by updating the weights in the connections between the input field and the procedure field. In the intervals of the activations of a newly selected category node in the procedure field, a graded pattern of activation values is calculated by sequencing with a decaying factor. The pattern with the task identity information of the channels directly from the input represents a task [12]. The temporal procedures and the information from the input are encoded as a task by adjusting the weights between the procedure field and the event/task field. In a similar manner, a series of activations in the event/task field is encoded as an episode. Through the sequencing process, the activation values in the event/task field form a graded pattern, and this pattern with the directly connected inputs including the subjective time and/or place represents an episode. The pattern and the information directly from input representing an episode are encoded by updating the weights between the event/task field and the episode field.

Once an episode is recognized as a selected node in the episode field, the complete episode can be reproduced as a sequence of events or tasks by a top-down retrieval process from the episode field to the event/task field. When task-related cues, time information, and/or place information is given, the corresponding category node in the episode field is retrieved in a manner similar to how an episode is encoded, except the weights are updated in the I-ART memory model and the stored episode is finally read out from the network. The tasks in an episode can also be reproduced as a sequence of procedures. From a given sequence of procedures, the relevant task is chosen by the process from the input field to the event/task field without adjusting the weights, and the correct sequence of procedures is retrieved according to the category node in the event/task field. The computational processes of encoding, storing, and retrieving for task memory within episodic memory are described in detail in the next sections.

III. Task Memory Learning

When episodic memory is encoded, the sequential procedures for tasks in an episode are also stored as task memory in I-ART. The attributes of actions, objects, time, place, etc.

are encoded from input field F_1 and activate a category node in procedure field F_2. A graded pattern from the temporally activated nodes in F_2 is encoded in event/task field F_3. To retrieve the procedures from the memory encoded as episodes, with a given sequence of procedures with the attributes, the category nodes in F_2 are activated in serial order and form a graded pattern. From the pattern, the corresponding category node in F_3 that represents the corresponding task is selected and all procedures for the task are retrieved by a top-down retrieval process.

A. Fusion ART

I-ART employs three fusion ART networks to select and activate a category node correspondingly for each procedure, task, and episode. The fusion ART network is used to learn individual procedures with a set of universal computational processes for the encoding, recognition, and reproduction of patterns, and encodes procedures as the weighted connections between the attributes from multichannel input and the corresponding category. Each category is characterized by an activity value. The process to match and activate each category node from the input vector is described in the following five stages.

1) Complement coding: The vector received for each channel of the input layer, $\mathbf{X}^k = (x_1^k, x_2^k, \cdots, x_{2n}^k) = (\mathbf{I}^k\, \bar{\mathbf{I}}^k)$ is the concatenated form of the input vector, $\mathbf{I}^k = (I_1^k, I_2^k, \cdots, I_n^k)$ such that $I_i^k \in [0, 1]$ for $k = 1, 2, \cdots, n$ and its complement vector $\bar{\mathbf{I}}^k = (\bar{I_1}^k, \bar{I_2}^k, \cdots, \bar{I_n}^k)$ such that $\bar{I_i}^k = 1 - I_i^k$.

2) Code activation: The activity value of the jth output node associated with the received vector $\mathbf{X}^k$ is determined as follows:

$$T_j = \sum_{k=1}^{n} \gamma^k \frac{|\mathbf{X}^k \wedge \mathbf{W}_j^k|}{(\alpha^k + |\mathbf{W}_j^k|)} \tag{1}$$

where $\alpha^k \geq 0$ is a choice parameter, $\gamma^k \in [0, 1]$ is a contribution parameter, $\mathbf{W}_j^k$ is a weight vector, the fuzzy AND operator $\wedge$ is defined as $(\mathbf{A} \wedge \mathbf{B})_i \equiv min(a_i, b_i)$, and the norm $|\cdot|$ is defined as $|\mathbf{A}| = \sum_i a_i$.

3) Code competition: The Jth node of the largest activity value among all activity values derived during the stage of code activation is selected as follows:

$$T_J = max\left\{T_j : \text{for all } F_2^{fusion} \text{ node } j\right\} \tag{2}$$

As a node is selected as a category, an output value of 1 is set for the chosen node. The other nodes have output values of 0.

4) Template matching: Each selected Jth node is checked according to its resonance value. If the resonance value is larger than a vigilance parameter $\rho^k \in [0, 1]$, the Jth node is selected finally. If not, a new node is committed to be activated. Template matching is performed as follows:

$$m_J^k = \frac{|\mathbf{X}^k \wedge \mathbf{W}_J^k|}{|\mathbf{X}^k|} \geq \rho^k \tag{3}$$

Algorithm 1 Task Encoding

for each procedure involved in an task **do**
  select a category node J in F_2 based on input vectors from F_1 through fusion ART
  let the activity value for the selected node as $y_J = 1$
  for each previously selected node y_j in F_2 **do**
    apply decaying factor as $y_j^{(new)} = (1 - \tau) y_j^{(old)}$
  end for
end for
given an input vector of a sequence of procedures in F_2
select a category node J' in F_3 based on input vectors through fusion ART
update the weight vector with $\mathbf{W}_{J'}^k = (1 - \beta^k)\mathbf{W}_{J'}^{k(old)} + \beta^k(\mathbf{X}^k \wedge \mathbf{W}_{J'}^{k(old)})$

Algorithm 2 Task Retrieval

for each incoming procedure **do**
  select a category node J in F_2 based on given vectors from F_1 through fusion ART
  let the activity value for the selected node as $y_J = 1$
  for each previously selected node y_j in F_2 **do**
    apply decaying factor as $y_j^{(new)} = (1 - \tau) y_j^{(old)}$ or $y_J = 1$ if $y_j^{(old)} < 0$
  end for
  select a category node J' in F_3 based on a sequence of procedures through fusion ART
  if J' is found **then**
    exit
  end if
end for

5) Template learning: If template matching is accomplished, the weight vector is then updated as follows:

$$\mathbf{W}_J^k = (1 - \beta^k)\mathbf{W}_J^{k(old)} + \beta^k(\mathbf{X}^k \wedge \mathbf{W}_J^{k(old)}) \tag{4}$$

where $\beta^k \in [0, 1]$ is the learning rate.

B. Sequencing

To include temporal information in procedures and tasks, the technique of sequencing is used between each fusion ART of the I-ART. After node y_J is newly selected through a fusion ART network, the activity values of previously selected nodes are multiplied by $(1 - \tau)$ before a new node $y_{J'}$ is selected, where τ is a decaying factor. With this sequencing process, a graded pattern of activity values of category nodes is generated, and it can be observed as the order of how the procedures or tasks occurred. The calculated sequential pattern is used as an input for another fusion ART network.

C. Task Encoding

The attributes of each incoming procedure composing a task are encoded in F_1. Based on the input vector in F_1, the corresponding node in F_2 is selected and activated through the matching and activating process of a fusion ART. The newly selected category node y_J is then given the activity value of 1, and the previously selected nodes form a graded pattern through a sequencing process with the decaying factor τ. After all procedures of a task are encoded, the calculated graded pattern of the activity values of selected category nodes in F_2 becomes an input to the fusion ART connecting F_2 and F_3. Finally, the corresponding task node in F_3 is selected, and the node represents the task. The task encoding process is summarized as Algorithm 1.

D. Task Retrieval

When a sequence of procedures is provided, the complete sequence of procedures should be retrieved to perform the corresponding task. Thus, the task retrieval algorithm is provided as Algorithm 2 to retrieve the correct procedures of the corresponding task from an incoming sequence of procedures in I-ART. For each given incoming procedure, the category node in F_2 is activated, and a graded pattern of the sequential procedures is formed by sequencing. After the sequencing process, the corresponding task node in F_3 is selected for the graded pattern as an input by the activating and matching process of the fusion ART without updating the weight vector, and the correct procedures of the task are read out from the selected node.

IV. Episodic Memory Learning

From the activated task category nodes in F_3, a sequence of tasks is stored in episodic memory. After the task nodes in F_3 are selected and activated, the nodes have a graded pattern by sequencing with a decaying factor of τ, and the pattern is encoded in episode field F_4 with a subjective time and/or place from F_1. The subjective time can be predefined by four types of vectors: year, month, date, and time vectors. The selected episode category node in F_4 represents the corresponding episode. There are two cases to retrieve episodic memory in I-ART. When every encoded input is given, the relevant episode is retrieved. The sequence of tasks, subjective time, and place are used as the input in F_3 to find the corresponding episode node in F_4. With the retrieved node, the episode is reproduced. In the other case, due to the definition of episodic memory, I-ART allows travel to a certain situation when retrieving episodes from either task-related cues, a subjective time, or a place. With a given input among them, the corresponding category node in F_4 is selected and the episode encoded on the node is read out.

A. Episode Encoding

After the tasks are memorized as an episode, the encoded tasks by the task encoding process in F_3 compose an episode in F_4 with the information of a subjective time and a place. The tasks for an episode are encoded by activating the task category nodes in F_3 sequentially, and the temporal tasks are expressed as a graded pattern of the activity values of the nodes in F_3 by the sequencing process. A subjective time and a place provided directly from F_1 are combined with the generated graded pattern of the tasks as the inputs to encode an episode in F_4. In other words, the calculated graded pattern of the tasks, subjective time, and place are used to select and activate the episode node in F_4 by the matching and activating processes of a fusion ART. The chosen episode category node in F_4 then represents the encoded episode and includes not only the information of the tasks, subjective time, and place but also the sequences of procedures. The tasks as an episode are classified and stored in the episode category node, and each task stores the corresponding sequence of procedures through the procedure field and the event/task field. The episode encoding process is summarized as Algorithm 3.

Algorithm 3 Episode Encoding

for each task involved in an episode **do**
  select a category node J in F_3 based on an input vector of a sequence of procedures in F_2 through fusion ART
  let the activity value for the selected node as $y_J = 1$
  for each previously selected node y_j in F_3 **do**
    apply decaying factor as $y_j^{(new)} = (1-\tau)y_j^{(old)}$
  end for
end for
given an input vector, concatenated a sequence of tasks in F_3 with time and/or place vectors from F_1
select a category node J' in F_4 based on input vectors through fusion ART
update the weight vector with $\mathbf{W}_{J'}^k = (1-\beta^k)\mathbf{W}_{J'}^{k(old)} + \beta^k(\mathbf{X}^k \wedge \mathbf{W}_{J'}^{k(old)})$

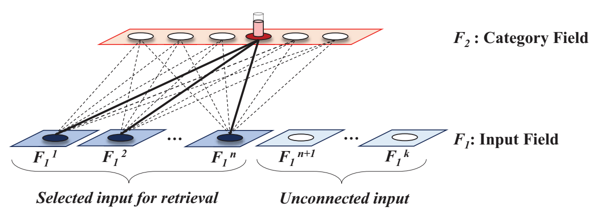

Fig. 2. Selected input retrieval in I-ART.

B. Selected Input Retrieval

In the I-ART memory model, the inputs from different fields are connected and used to select the category node. According to the connecting field, the input can be used as a cue for retrieval. To retrieve episodic memory with a selected input, it is assumed that only selected input nodes are connected to the category field while other nodes are not. With this assumption, the influence of unconnected nodes can be removed, as shown in Fig. 2. In I-ART, the weights associated with unconnected nodes are simply suppressed as zero vectors, as the zero vectors of weights remove the influence of unconnected inputs during the activating process of a fusion ART according to (1) in the stage of code activation.

Algorithm 4 Episode Retrieval with Tasks/Subjective Time/Place

given input
let the weight vectors associated with the rest as $\mathbf{W}_j^k = \mathbf{0}$ in fusion ART between F_3 and F_4
select a category node J in F_4 based on the input through fusion ART
if J is found **then**
    exit
end if

C. Episode Retrieval

In I-ART, the episodic memory retrievals can be classified into two cases: when every encoded input is given or partial input among all is given. Episodes can be retrieved with every encoded input; it is similar to the process used in the EM-ART memory model. For each given task-related cue in an episode, the task node in F_3 is selected by the matching and activating process of a fusion ART. Through this sequencing process, the selected nodes in F_3 form a graded pattern of tasks, and the corresponding episode is then selected according to the every encoded input including the pattern. The other case is to retrieve the episode from either task-related cues, a subjective time, or a place, and the method is summarized as Algorithm 4. With a given input, the fusion ART connecting F_3 and F_4 is retrieved. Since the corresponding episode is retrieved only with the selected input, the weight vectors associated with the rest are suppressed as zero vectors. From the suppressed network, the episode is retrieved from the given input by the activating and matching process of a fusion ART without updating the weight vector. Finally, the corresponding episode is read out.

V. Comparison Study

In this section, the proposed I-ART was compared with the other spatio-temporal memory methods for the performance. As far as authors' knowledge goes, the fully implemented method that integrates two types of memory systems has not been presented, so for comparison purpose, we separated the I-ART network into the task memory part and the episodic memory part, and compared each part as a spatio-temporal memory to the other methods. The robustness and error tolerance were verified for the typoglycemia phenomena benchmark that a misspelled word is recognized as the correct word. The benchmark problem is presented in [17].

In the comparison study, the correct 73 words were used as training data, and the misspelled 107 words were used as test data. Each word was encoded through an input channel as a vector which has 26 binary bits representing each alphabet. The vigilance values for an alphabet and a word were set to 1 in both memory parts. To test the task memory part in I-ART, each alphabet among the sequentially obtained alphabets per word was classified into a procedure category node in the procedure field, and the graded pattern of the alphabets by the sequencing process was stored in the event/task field. When a misspelled word was given, the correct word node was retrieved as the most nearest task category node under the vigilance value. This method verified the performance of the task memory part in I-ART to store a temporal information effectively and to retrieve the purposed information even with noised inputs. Similarly, to verify the performance of the episodic memory part in I-ART, each alphabet was encoded into a task category node, and the temporal pattern of the alphabets per word generated by the sequencing process was encoded into an episode node.

As recognizing a misspelled word as the correct word, the performance was verified. For the performance verification, the word recognition accuracies were evaluated as the ratios of the successfully matching number of words to the number of the tested words. The compared other methods were EM-ART, LTM, a hidden Markov model (HMM), and Levenshtein distance method of which resulted word recognition accuracies were 100%, 100%, 94.67% and 89.36%, respectively. The detailed setting and resulted accuracies for the other methods were from the other papers [10], [12]. On the other hand, the accuracies of the task memory part and the episodic memory part in I-ART were 100%, which is comparable to the other spatio-temporal memory systems.

Despite the integration of two different memory systems to encode task memory and episodic memory simultaneously and retrieve the memories separately according to the inputs to the memory model, each memory part performed comparably. Especially, I-ART performs comparably to EM-ART which constituting each memory part in the I-ART network. This result shows that the performance of each memory part does not decrease, even though two different memory systems are integrated. That is, our proposed I-ART takes advantage of integrating episodic memory with task memory, while keeping high performance of the robustness and error tolerance of each memory system.

VI. Simulation and Experimental Results

The proposed memory model, called I-ART, is designed to integrate episodic memory with task memory in a single model. Using I-ART, a robot can store the memory of experienced episodes, including the procedures composing the tasks, as part of the episodes. Thereby, the robot is able to learn how to perform tasks from its experiences or can learn from the user's demonstration. By retrieving a sequence of procedures for a task encoded in an episode at a subjective time and/or place, the robot can retrieve a sequence of procedures to perform the task. In this section, the effectiveness of I-ART encoding episodic memory with task memory simultaneously and retrieving the memories separately, is demonstrated through computer simulations and experiments using the humanoid robot, Mybot-KSR2.

A. Simulation Setup

The designed I-ART memory model was applied to learn 20 different episodes with different subjective times. Each episode was a combination of events and/or tasks. Each task is chosen among 8 tasks composed of procedures as follows.

- *Water a flower: Grasp a watering pot, Move the watering pot to a flower, Tip the watering pot toward the flower, Put down the watering pot on the table*
- *Take out a book from a shelf: Move to a shelf, Approach the shelf, Grasp a book, Take down the book from the shelf*
- *Pour drink: Grasp a bottle, Open the bottle, Move the bottle to a bowl, Pour the bottle into the bowl, Close the bottle, Put down the bottle on a table*
- *Put a toy into a box: Grasp a to, Move the toy to a box, Put down the toy into the box*
- *Toast a slice of bread: Grasp a slice of bread, Move the bread to a toaster, Put down the bread into the toaster, Grasp the toaster, Push down the toaster*
- *Serve cereal: Approach a table, Grasp a milk pot, Move the milk pot to a bowl, Pour the milk pot into the bowl, Put down the milk pot on the table, Grasp a cereal box, Tip the cereal box toward the bowl, Put down the cereal box on the table*
- *Vacuum a room: Go to a room, Approach a vacuum cleaner, Grasp the vacuum cleaner, Turn on the vacuum cleaner, Go around the room with the vacuum cleaner, Turn off the vacuum cleaner, Put down the vacuum cleaner on the floor*
- *Make a bed: Approach a bed, Grasp a pillow, Put down the pillow on the bed, Grasp a blanket, Spread the blanket*

In addtion to tasks, events not related to task procedures were chosen among {*Go to garden, Feed dog, Play with dog, Wash dog, Go to kitchen, Go to bedroom, Call user, Wash dish, Approach user, Approach dog, Set morning call,* and *Wash dog*} to encode various episodes. All inputs were expressed as vectors that are composed of binary bits, and the corresponding bit expressing a certain attribute was set to 1 with the others set to 0. In the I-ART memory model, six input channels in total were used respectively for actions, objects, task identity, month, date, and time vectors to encode episodes. Among them, two input channels were used to encode actions among 15 actions and objects among 19 actions to represent a procedure.

The time of which past and future moments are involved was referred to as subjective time because past and future, the bases of humans' travel in their minds, are the products of the human minds [19], [20]. For this reason, a subjective time was predefined subjectively with three types of vectors: month, date, and time vectors that have 12 binary bits, 31 binary bits, and 4 binary bits, respectively. The 4 binary bits were used to represent the time that is classified into {*morning, afternoon, evening, night*}. Place was not considered in the simulations.

For the simulations, the I-ART network was trained to store episodes that contains tasks composed of corresponding procedures. Based on the inputs of action, object, and time encoded in the input field referring to individual procedures, the network was trained to classify the procedures in the procedure field, and stored the temporal procedures encoded as the corresponding task in the task field. The temporal tasks were stored as an episode along with a subjective time in the episode field. From the I-ART, the sequences of procedures for a task stored in the task memory part were retrieved for a robot to perform the task, whereas the temporal tasks stored as an episode in the episodic memory part were retrieved to help the robot to remember the past experience happened at a subjective time.

TABLE I
TASK RETRIEVAL ACCURACIES (IN %) WITH PROCEDURE CUES

Task retrieval with partial procedure-related cues	
Procedure-related cue lengths (ρ_{action}, ρ_{object}, ρ_{task}) = (0.9, 0.95, 0.95)	Accuracy (%)
Full length	100
Three-quarter length from the beginning	100
Half-length from the beginning	100
Three-quarter length from the end	100
Half-length from the end	75
Three-quarter length from an arbitrary location	100
Half-length from an arbitrary location	94

Once a learning process had been conducted, the performance of the I-ART network was evaluated by applying various types of retrieval cues. The accuracy of the trained I-ART memory model was calculated from the number of successful retrievals in each case. Choice parameter α, contribution parameter γ, learning rate β, and vigilance parameter ρ determine the dynamics of the network. For the inputs that are equally influential in selecting the corresponding category node, the same α and γ were employed. β determines how much the fusion ART updates its weight vectors for given inputs, and β less than 1 makes the network to tolerate the noise in inputs. ρ is the threshold value that determines whether the given inputs are matched to a certain node. The larger ρ, the more accurate the matching becomes, but the lower the error tolerance becomes. A decaying factor τ determines how a graded pattern is generated from sequentially activated category nodes. As τ decreases, the graded pattern encoding which node is activated in which order becomes more recognizable. As τ increases, the capacity of a graded pattern increases, which denotes how many node activation values are stored. For all simulations, γ for procedure encoding, γ for task and episode encodings, α, β, and τ were set to 0.4, 1, 1, 0.8, and 0.2, respectively. The vigilance parameters for actions, objects, tasks, and episodes are provided in Tables I and II.

B. Simulation Results

The results of the simulations are presented in Tables I and II for retrieval accuracies.

1) Task memory retrieval with procedure-related cues: In this simulation, partial sequences of the encoded procedures composing the tasks were used as cues to retrieve the correct procedures. There were seven cases of cues, i.e., full-length cues, three-quarter-length and half-length partial cues from the beginning, three-quarter-length and half-length partial cues from the end, and three-quarter-length and half-length partial cues from an arbitrary location. For most cases, the procedures were retrieved with 100% accuracy, except for the cases of the half-length cues from the end and from an arbitrary location, as shown in Table I. This demonstrates that the procedures of the tasks encoded as episodes were retrieved

TABLE II
EPISODE RETRIEVAL ACCURACIES (IN %) WITH TASK CUES AND/OR SUBJECTIVE TIME

Episode retrieval with partial task-related cues	
Task-related cue lengths (ρ_{task}, ρ_{epi}) = (0.95, 0.9)	Accuracy (%)
Full length	100
Three-quarter length from the beginning	100
Half-length from the beginning	95
Three-quarter length from the end	100
Half-length from the end	25

Episode retrieval with subjective time cues	
Subjective time (ρ_{time}, ρ_{epi}) = (0.9, 0.9)	Accuracy (%)
Full length	100

Episode retrieval with task and subjective time cues	
Task-related cue lengths (ρ_{task}, ρ_{time}, ρ_{epi}) = (0.95, 0.9, 0.9)	Accuracy (%)
Full length	100
Three-quarter length from the beginning	100
Half-length from the beginning	95
Three-quarter length from the end	100
Half-length from the end	100

separately and effectively even with partial procedure-related cues. Additionally, the reward channel connected from the input to the procedure field can be utilized to improve the retrieval capability [21].

2) Episodic memory retrieval with task-related cues: In this simulation, partial sequences of the encoded tasks were employed as cues to retrieve the corresponding episode. There were five cases of cues, i.e., full-length cues, three-quarter-length and half-length partial cues from the beginning, and three-quarter-length and half-length partial cues from the end. Except for the half-length cues from the end, the retrieval accuracies were 100% or nearly 100%, as shown in Table II. This demonstrates that the tasks of each encoded episode were retrieved with the given task-related cues even if time information was not given.

3) Episodic memory retrieval with subjective time: In this simulation, time vectors used for learning as a subjective time were employed as cues to retrieve the corresponding episode. According to the given time vectors, the corresponding episode category node was selected by choosing the largest activity value. The accuracy, as shown in Table II, was 100% with the time vectors used for learning as a subjective time. This demonstrates that the encoded episodes were retrieved with the given time information even if task-related cues were not given.

4) Episodic memory retrieval with task-related cues and subjective time: In this simulation, both partial task-related cues and time vectors used for learning as a subjective time were employed as cues to retrieve the corresponding episode. Five cases of task-related cues, i.e., full-length cues, three-quarter-length and half-length partial cues from the beginning, and three-quarter-length and half-length partial cues from the end were given with the time vectors. As shown in Table II, the retrieval accuracies were nearly 100% and were especially improved compared to the episode retrieval results only with partial task-related cues. This demonstrates that the encoded episodes were retrieved with every encoded cue more accurately than with partial cues.

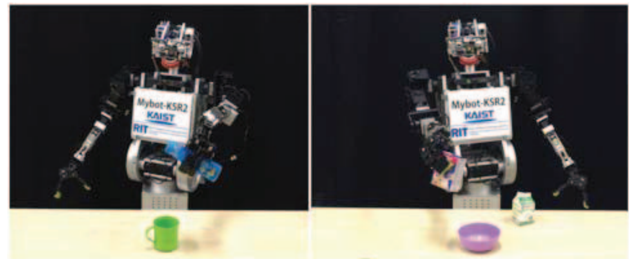

Fig. 3. Mybot-KSR2 performing *Pour drink* and *Serve cereal* tasks.

C. Experimental Results

The I-ART network was implemented on the humanoid robot, Mybot-KSR2, developed in the RIT Lab. at KAIST as shown in Fig. 3. An RGB-D camera is in the robotic head of Mybot-KSR2 for vision. The upper body is comprised of a torso of 2 DoFs and two arms each of 10 DoFs. The algorithm on Mybot-KSR2 to perceive objects and actions done by an instructor for teaching the robot was from the earlier work [18]. In the experiment using Mybot-KSR2, we trained the I-ART network for *Pour drink* and *Serve cereal* tasks as an episode by showing the sequential demonstrations for the two tasks. Each task was shown as consecutive procedures in a demonstration, and each procedure was perceived as a pair of an action and related objects. The robot performed the corresponding task, when the related objects were perceived, by retrieving the procedures of the task from the I-ART network.

The temporal procedures perceived by Mybot-KSR2 in the robot's view are shown in Fig. 4. After Mybot-KSR2 stored the procedures of the two tasks as an episode in the I-ART network, for the perceived objects in front of the robot, it retrieved the temporal procedures of the corresponding task from the task memory part in the I-ART. Based on the retrieved sequence of procedures, Mybot-KSR2 performed the task. The video clips for learning and retrieval by Mybot-KSR2 have been uploaded as a supplementary file.[1]

VII. CONCLUSION

This paper proposed a novel neural memory model, termed I-ART, to integrate episodic memory with task memory. The sequences of procedures were encoded in task memory, while the tasks composing episodes were encoded with a subjective time and/or a place in episodic memory. Task memory was

[1]The video is available at: `http://rit.kaist.ac.kr/home/I-ART`

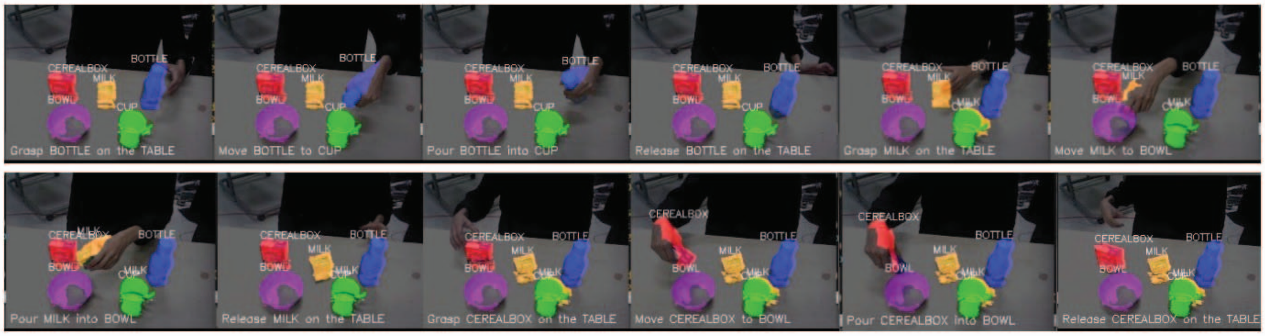

Fig. 4. Temporal procedures in demonstration in the view of Mybot-KSR2.

retrieved with procedure-related cues, and episodic memory was retrieved with task-related cues, the time, and/or the place information. Comparison study with other memory systems demonstrated that the proposed I-ART shows high performances of the robustness and error tolerance for each memory part even while taking advantage of implementing episodic memory with task memory in a single model. Computer simulations and experiments with the humanoid robot, Mybot-KSR2 were conducted with I-ART for episodes to be encoded and procedures of the corresponding task and tasks of the corresponding episode to be retrieved. The results demonstrated that the procedures of tasks as well as the tasks in episodes could be stored together in the I-ART network and retrieved separately from partial cues with high accuracy. Simulations also showed that the subjective time as a key concept defining episodic memory could be used as a cue for retrieving episodic memory in the I-ART memory model.

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