ISSN : 2347 - 8446 (Online)
ISSN : 2347 - 9817 (Print)

Neural Networks Modeling of Memory Based information Encoding, Retrieval and Forgetting Methods

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Abstract

This paper presents a neural model that learns episodic traces in response to a continuous stream of sensory input and feedback received from the environment. The proposed model, based on fusion adaptive resonance theory (ART) network, extracts key events and encodes spatio-temporal relations between events by creating cognitive nodes dynamically. Combined with a mechanism of gradual forgetting, the model is able to achieve a high level of memory performance and robustness, while controlling memory consumption over time. where the proposed episodic memory model is evaluated based on the memory consumption for encoding events and episodes as well as recall accuracy.

Keywords

Adaptive Resonance Theory-Based Network, Agent, Episodic Memory, Forgetting, Hierarchical Structure, Memory Robustness, Unreal Tournament.

I. Introduction

EPISODIC memory is a special class of memory system that allows one to remember his/her own experiences in an explicit and conscious manner [1]. Although episodic memory is considered to be less important than semantic memory, recent research has found episodic memory to be crucial in supporting many cognitive capabilities, including concept formation, representation of events in spatio-temporal dimension, and record of progress in goal processing [2]. In particular, Morgan and Squire have shown that during reinforcement learning tasks, hippocampus (an area of the brain believed to be the place of episodic memory) is critical for representing relationships between stimuli independent of their associations with reinforcement [3]. The specifi functionalities mentioned above suggest that episodic memory should not be just a storage of one's past experiences, but should support the representation of complex conceptual and spatio-temporal relations among one's experienced events and situations. In this paper, we present a computational model called electromagnetic adaptive resonance theory (EM-ART) for encoding of episodic memory in terms of events as well as spatio-temporal relations between events. The model can be incorporated into an autonomous agent for encoding its individual experience, which can be retrieved later for reasoning in real time. Based on a generalization of fusion adaptive resonance theory (ART) [9], the EM-ART model supports event encoding in the form of multiple-modal patterns. An episodic encoding scheme is introduced that allows temporal sequences of events to be learned and recognized. The forgetting mechanism removes unimportant and outdated events from the episodic memory and enables the model to maintain a manageable level of memory consumption over a possibly infinite time period. This is a feature crucially required by real-time systems.We have conducted experimental studies on the proposed model through two different applications. The first application is a word recognition task, wherein the proposed model is used to learn a set of words. The performance is measured by the accuracies of retrieving the learned words given their noisy versions. Compared with existing models of Spatio-temporal memory, the experiment results show that the EM-ART model is one of the best models in terms of retrieval performance. EM-ART is used to learn episodic memory based on an agent's encounters in the game. This is in comparison with the long term memory (LTM) model, which is another best performing model in the word recognition task.

II. Methodology

A. Memory Formation

There are two basic elements of episodic memory that are events and episodes. An event can be described as a snapshot of experience. Usually, by aggregating attributes of interest, a remembered event can be used to answer critical questions about the corresponding experience, such as what, where, and when. On the other hand, an episode can be considered as a temporal sequence of events. To enable efficient encoding of events and episodes, an episodic memory model should be able to distinguish between distinct events and episodes with a well-defined matching scheme. The critical characteristic for the matching scheme is its high efficiently in determining the significant differences while tolerating all minor variances for both events and episodes encoding. Therefore, an efficient matching scheme should also lead to a parsimonious memory storage as well as faster memory operations.

B. Memory Retrieval

There are three identify major tasks in episodic memory retrieval, namely event detection, episode recognition, and episode recall, described as follows. Event detection refers to the recognition of a previously learned event based on a possibly incomplete description of the current situation. The episodic memory model should be able to search for similar memorized events, which can be used to complete or refine the given description. Episode recognition refers to the identification of a stored episode in the episodic memory in response to a partial event sequence. Two basic requirements of episode recognition include: 1) tolerance to incomplete cues, which only form parts of the stored episodes and 2) tolerance to errors, for example, noise in event attributes and variations in the order of event sequences. Episode recall is the playback of episode(s) in response to an external cue, such as "what did I do yesterday?, episodic memory answers the cue with the most closely matched episode according to its similarity. During the episode playback, compared with the stored information. The episodic memory model should be able to identify and tolerate this imperfection during recall.

C. Forgetting

Many studies have indicated that the memory traces in the hippocampus are not permanent and are occasionally transferred to neocortical areas in the brain through a consolidation processes. This implies that forgetting should exist in episodic memory to avoid possible information overflow. Forgetting in the episodic memory helps to preserve and strengthen important or frequently used episodes, and remove (or forget) unimportant ones. More importantly, it is a necessary condition for promoting efficient memory storage, as well as fast and accurate operation of episodic memory in real-time environments.Taking the above into consideration, an episodic mem- ory model should satisfy the following basic requirements:
1) efficient event representation describing complex situations and events; 2) efficient episode representation for exploring spatio-temporal relations among events which form the episode; 3) well-defined generalizations on representations, which accurately distinguish critical and irrelevant differences among them (for both events and episodes); 4) high level of tolerance to incomplete or noisy cues; 5) fast memory operations, including memory encoding and retrieving; 6) tracking the importance of events and episodes in real time based on rewards, surprises, emotions, interpretation, and access frequency; and 7) forgetting mechanism to deal with the limited memory capacity.

III. Proposed Model

Our proposed episodic memory model, called EM-ART, is built by hierarchically joining two multichannel self- organizing fusion ART neural networks. Based on ART [13]. As shown in Fig. 1, the model consists of three layers of memory fields: F1, F2, and F3. The F1 layer is connected with the working memory to hold the activation values of all situational attributes. Based on the F1 pattern of activations, a cognitive node in F2 is selected and activated as recognition of the event. Following that, the activation pattern of an incoming event can be learned by adjusting the weights in the connections between F1 and F2 .

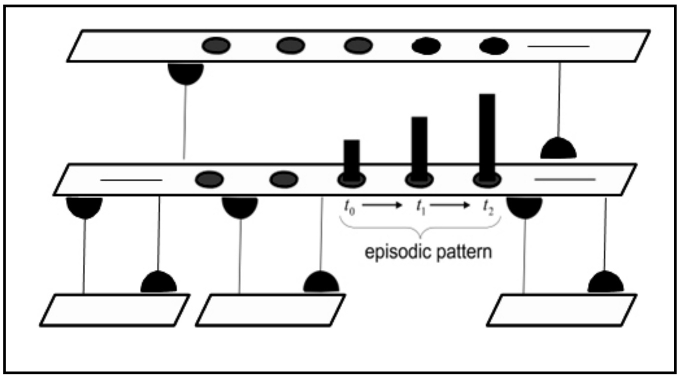

Fig.1: Proposed neural network architecture of the Episodic models.

The F2 layer also acts as a medium-term memory buffer for event activations. A sequence of events produces a series of activations in F2 . The activations in F2 decay over time such that a graded pattern of activations is formed representing the order of the sequence. This activity pattern, which represents an episode, is similarly learned as weighted connections between F2 and the selected category in F3.
Once an episode is recognized through a selected node in F3, the complete episode can be reproduced by a top down activation process (readout) from F3 to F2. The events in the episode can also be reproduced by reading out the activations from F2 to F1 following the order of the sequence held in the F2 layer.
An event consists of attributes characterizing what, where, and when an event occurs. Fig. 2 shows an example of the structure of an input event based on the Unreal Tournament domain [16]. This structure is also used in the experiments for evaluating EM-ART.

Event Encoding And Retrieval

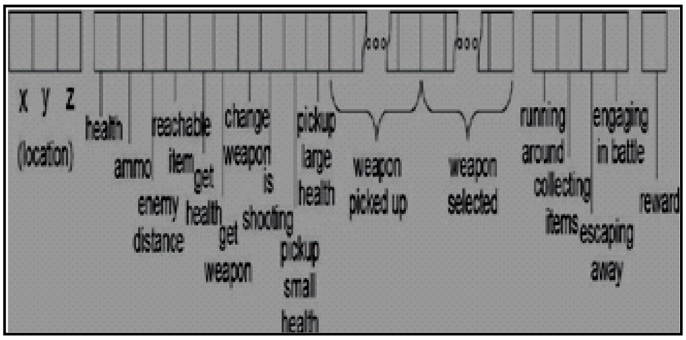

Fig. 2 : Event encoding

An event consists of attributes characterizing what, where, and when an event occurs. Fig. 2 shows an example of the structure of an input event based on the Unreal Tournament domain [16]. This structure is also used in the experiments for evaluating EM-ART.

A. Fusion ART

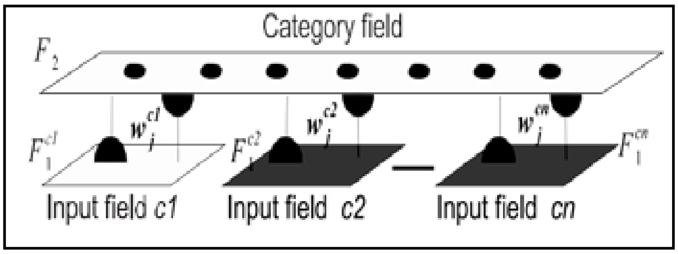

Fig. 3: Fusion ART architecture

Fusion ART network is used to learn individual events encoded as weighted connections between the F_1 and F_2 layers. Fig.3 illustrates the fusion ART architecture, which may be viewed as an ART network with multiple input fields.

Input Vectors: Let $\mathbf{I}^k = (I_1^k, I_2^k, \ldots I_n^k)$ denote an input vector, $I_i^k \in [0,1]$ indicates the input i to channel k, for k=1,2,...n. With complement coding, the input vector $\mathbf{I}^k$ is augmented with a complement vector $\bar{\mathbf{I}}^k$ such that $\bar{\mathbf{I}}^k = 1 - \mathbf{I}^k$.

Input Fields: let F_i^k denote an input field that holds the input pattern for channel k. Let $\mathbf{x}^k = (x_1^k, x_2^k, \ldots x_n^k)$ be the activity vector of F_1^k receiving the input vector $\mathbf{I}^k$ (including the complement).

ISSN : 2347 - 8446 (Online)
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Category Fields: Let F_i denote a category field and $i > 1$ indicate that it is the ith field. The standard multichannel ART has only one category field, which is F_2. Let $\mathbf{y} = (y_1, y_2, \ldots, y_m)$ be the activity vector of F_2.

Weight Vectors: Let wjk denote the weight vector associated with the j th node in F2 for learning the input pattern in F_1^k.

Parameters: Each field's dynamics is determined by choice parameters $\alpha^k \geq 0$, learning rate parameters $\beta^k \in [0,1]$, contribution parameters $\gamma^k \in [0,1]$, and vigilance parameters $\rho^k \in [0,1]$.

Code Activation: A node j in F_2 is activated by the choice function

$$T_j = \sum_{k=1}^{n} \gamma^k \frac{|x^k < w_j^k|}{\alpha^{k+|w_j^k|}}$$

Code Competition: A code competition process selects a F_2 node with the highest choice function value. The winner is indexed at J where

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

When a category choice is made at node J, $y_J = 1$; and $y_j = 0$ for all $j = J$ indicating a winner-take-all strategy.

Algorithm 1 Event Encoding and Retrieval

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1 Given an input pattern of event as vector $\mathbf{I}^k$ in F_1

2 Activate every node j in F_2 by choice function

$$T_j = \sum_{k=1}^{n} \gamma^k \frac{|x^k < w_j^k|}{\alpha^{k+|w_j^k|}}$$

3 select node J such that $TJ = \max\{Tj : \text{for all } F2 \text{ node } j\}$,

4 set node activation $y_J \leftarrow 1$

5 WHILE match function $m_j^k = \frac{|x^k < w_j^k|}{|x^k|} < \rho^k$

6 deselect and reset J by $T_J \leftarrow 0$, $y_J \leftarrow 0$

7 select another node J with $TJ = \max\{Tj : \text{for all } F2 \text{ node } j\}$

8 IF no matching (resonance) J can be found in F_2

9 THEN let $J \leftarrow J^0$, where J^0 is a newly recruited uncommitted node in $F2$

10 learn J as a novel event with $\mathbf{w}_J^{k(new)} = \mathbf{x}^k$

The recognition task can be realized by a bottom-up activation given the input vector, using the standard operations of fusion ART. On the other hand, the top-down activation (readout operation) achieves the recall task. The bottom-up and top-down operations for learning, recognition, and recalling an event.

More specifically, the algorithm for learning and recognizing events can be described as Algorithm 1.

Algorithm 2 Episode Activation and Learning

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1 FOR EACH subsequent event in episode S

2 select a resonance node J in F_2 based on input $\mathbf{I}^k$ in F_1

3 let node activation $y_J \leftarrow 1$ (or a predefined maximum value)

4 FOR EACH previously selected node i in F_2

5 decay its activation by $y_j^{(new)} = y_j^{(old)(1-\tau)}$ or 0 if $y_j^{(old)} \leq 0$

6 Given activation vector $\mathbf{y}$ formed in F_2 after the subsequent presentation of S

7 select a resonance node J' in F_3 based on Activation vector $\mathbf{y}$

8 learn its associated weight vector as $\mathbf{w}'^{(new)} = \mathbf{y}$ if S is a novel episode

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The process of episode learning in EM-ART While a newly activated node has an activation of 1, the activation value of any other node j in F_2 is decayed in each time step so that $y_j^{(new)} = y_j^{(old)(1-\tau)}$ where y_j is the activation value of the jth node in F_2 and $\tau \in (0, 1)$ is the decaying factor.

Once an episode is recognized, the complete pattern of sequence can be reproduced readily in the F_2 layer by the read out operation from the selected node in F_3 to the nodes in F_2. However, to reproduce the complete episode as a sequence of events, the corresponding values in F_1 layer must be reproduced one at a time following the sequential order of the events in the episode. After the sequential pattern is read out to the field in F_2 which can be expressed as vector y, a complementing vector can be produced so that for every element i in the vector, $i = 1 - y_i$. Given the vector , the node corresponding to the largest element in is selected first to be read out to the F_1 fields. Subsequently, the current selected element in the vector is suppressed by resetting it to zero, and the next largest is selected for reading out until everything is suppressed. In this way, the whole events of the retrieved episode can be reproduced in the right order.

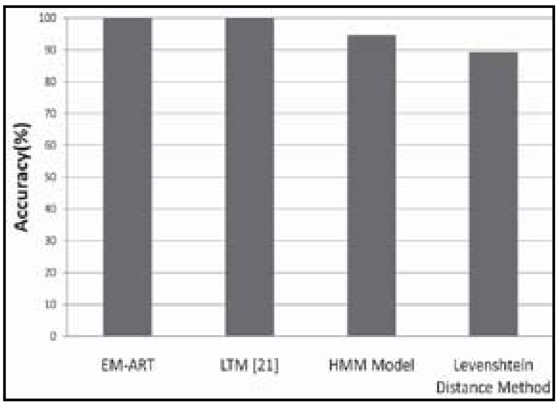
IV. Testing

Testing is used to compare the performance of the proposed model with other sequential memory methods for a word recognition task. In this task, we com- pare the performance of different models for the typoglycemia phenomena. To perform testing, each letter in the recognition test is fed into EM-ART model as an input vector one at a time. The input vector consists of 26 attributes, each of which represents a letter in the alphabet. At any time, only one attribute in the vector can be set to 1 to indicate the current letter read by the EM model. In the model, each letter is learned as an event node in F_1 , while a unique word is encoded as an episode node in F_2 describing the ordering of its included letters (i.e., events).

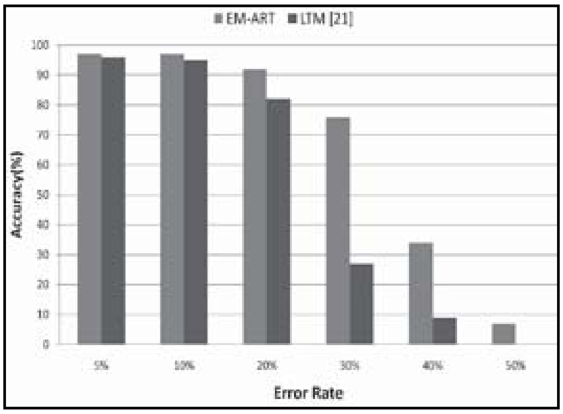
We trained the EM model using all corresponding corrected words indicated by the typoglycemia test. With a vigilance of 1 at both the event and episode levels (ρe = ρs = 1), the model creates 26 event nodes and 73 episodes nodes, which corresponds to the 26 letters and 73 unique words in the typoglycemia test. After building the EM model, we load the test passage with all the misspelled words. Therefore, the model performance can be examined by the memory retrieval subject to the noisy cues with erroneous ordering.

it can only achieve an accuracy of 89.36% in retrieving the typoglycemia text. HMM can correctly retrieve 94.67% of the learned words from all words in the test. However, it requires intensive training of each word as one model. Both EM-ART and LTM models have 100% retrieval accuracy. By further com- paring their space and time complexity, EM-ART employs less computational resources than LTM model to achieve the same level of retrieval performance. These results show that EM-ART provides better recognition.

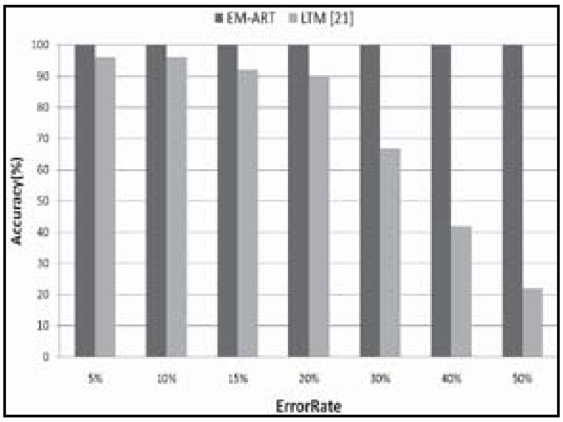
V. Results



Performance comparison on the word recognition



Performance comparison for retrieving with various error rates on event representation.



Performance comparison for retrieving with various error rates on sequence representation.

VI. Conclusion

We presented a new episodic memory model called EM-ART, based on a class of self-organizing neural networks known as fusion ART and the technique of invariance princi- ple. Since EM-ART allows the memory to grow dynamically by allocating a new category node for each new pattern, EM-ART is able to encode and learn the episodes with variabWe conducted empirical experimental evaluation on EM-ART using a fit-person shooting game, as well as a word recognition benchmark test. The experimental results showed that the model is able to provide a superior level of performance in encoding and recalling events and episodes even with various types of cue imperfections, including noisy and/or partial patterns.Our experiments on the synthetic data sets further revealed that EM-ART is especially robust in tolerating the variations in event sequences. In comparison, EM-ART does not generalize as well to noise at the event level. Finally, the experiments conducted also indicate that forgetting promotes an effective memory consolidation of its storage such that crucial knowledge can be kept in the memory, while the size of the stored information was regulated by discarding trivial and noisy information.

This paper has focused on the learning and retrieval functions within the episodic memory model. As discussed, episodic memory requires interactions with other related cog- nitive components to reveal its crucial roles. For example, the experiences stored in episodic memory may indicate more general knowledge in the form of a more permanent storage as semantic memory chunks. This indicates the potential of the co-evolving episodic-semantic model. Therefore, one immediate extension of our work is to

ISSN : 2347 - 8446 (Online)
ISSN : 2347 - 9817 (Print)

explore its interaction with other memory systems, especially semantic memory.

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