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ARTICLE IN PRESS

Neural Networks xxx (xxxx) xxx

Contents lists available at ScienceDirect

Neural Networks

journal homepage: www.elsevier.com/locate/neunet

Self-organizing neural networks for universal learning and multimodal memory encoding

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ARTICLE INFO

Article history:
Available online xxxx

Keywords:
Adaptive resonance theory
Universal learning
Memory encoding

ABSTRACT

Learning and memory are two intertwined cognitive functions of the human brain. This paper shows how a family of biologically-inspired self-organizing neural networks, known as fusion Adaptive Resonance Theory (fusion ART), may provide a viable approach to realizing the learning and memory functions. Fusion ART extends the single-channel Adaptive Resonance Theory (ART) model to learn multimodal pattern associative mappings. As a natural extension of ART, various forms of fusion ART have been developed for a myriad of learning paradigms, ranging from unsupervised learning to supervised learning, semi-supervised learning, multimodal learning, reinforcement learning, and sequence learning. In addition, fusion ART models may be used for representing various types of memories, notably episodic memory, semantic memory and procedural memory. In accordance with the notion of embodied intelligence, such neural models thus provide a computational account of how an autonomous agent may learn and adapt in a real-world environment. The efficacy of fusion ART in learning and memory shall be discussed through various examples and illustrative case studies.

1. Introduction

Learning and memory are two critically important and intertwined cognitive functions of the human brain. Whereas learning generally refers to the capability or process of converting the sensory signals received from the environment into knowledge which guides future performance, memory in the broad sense refers to the knowledge created internally as an outcome of the learning. While learning leads to the creation of new knowledge (or memory), memory in turn plays a critical role in high level cognitive functions, in particular situation awareness and decision making, enabling us to react to current situations based on our past experiences.

Learning and memory are intensively studied topics in the fields of cognitive psychology and computer science. Unsurprisingly, many distinct theories, models and methods have been proposed over the past decades. However, a unified account or theory is lacking in simulating and explaining various types of learning and memory capabilities of which a single human brain is capable of. In this paper, we show that a generalization of Adaptive Resonance Theory (ART), known as fusion Adaptive Resonance Theory (fusion ART), may serve as the building blocks of an integrated cognitive model that integrates a myriad of learning paradigms and memory systems.

Adaptive Resonance Theory (ART) (Carpenter & Grossberg, 1991, 2003; Grossberg, 1976a, 1976b) is a class of self-organizing neural networks derived from an analysis of human and animal perceptual and cognitive information processing. Besides applications to pattern recognition, analysis and prediction (Duda, Hart, & Stock, 2001; Levine, 2000), ART principles have led to behavioral and neurobiological predictions, which receive significant experimental support (Grossberg, 2003; Raizada & Grossberg, 2003).

Fusion ART, presented in this paper, is a direct extension of the single-channel ART models. Whereas ART models (Carpenter & Grossberg, 1987b) perform unsupervised learning of recognition categories from input patterns, fusion ART learns multi-channel associative mappings across multimodal pattern channels in an online and incremental manner. While fusion ART with a single input channel reduces to the original ART model, fusion ART with two or more pattern channels extends unsupervised learning to supervised learning, semi-supervised learning, multimodal learning, reinforcement learning, and sequence learning. More importantly, the knowledge learned by fusion ART can be interpreted as various types of memory systems as studied in the field

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https://doi.org/10.1016/j.neunet.2019.08.020
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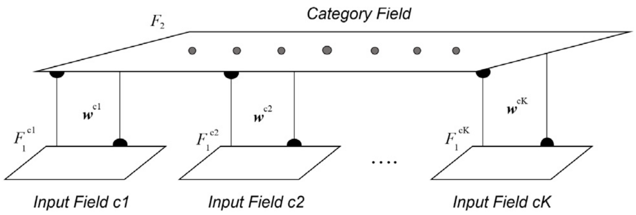

Fig. 1. The fusion ART network architecture.

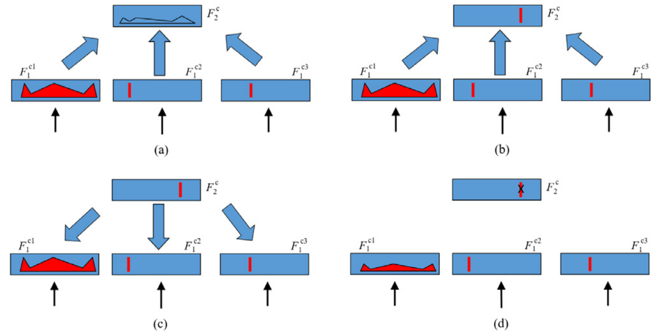

Fig. 2. The fusion ART dynamics: (a) Bottom up activation of category nodes; (b) Code competition in the category field; (c) Template matching and learning following a resonance; and (d) Reset of selected category node following an expectation mismatch in the F_1 fields.

of cognitive science, notably episodic memory, semantic memory and procedural memory.

Over the years, various forms of fusion ART models have been developed and applied to a wide range of applications, including personal profiling (Tan & Soon, 2000), text categorization (He, Tan, & Tan, 2003; Tan, Ong, Pan, Ng, & Li, 2004), gene expression analysis (Tan & Pan, 2005), social media clustering (Meng, Tan, & Xu, 2014), non-player character (NPC) modeling in games (Feng & Tan, 2016; Wang & Tan, 2015a), artificial human in virtual world (Kang, Tan, & Nah, 2012), computer generated forces (CGF) in combat simulation (Teng, Tan, & Teow, 2013), and simulating autobiographical memory. In this paper, we shall review the basic principles, models and algorithms of fusion ART and discuss how its network dynamics may support a principled account for a myriad of machine learning paradigms and memory representation.

The rest of the paper is presented as follows. Section 2 presents the basic fusion ART model and the associated system dynamics. Section 3 discusses how fusion ART can be employed in various forms of learning paradigms. Section 4 shows how fusion ART can be used to simulate various types of memory systems. To aid understanding, Section 5 presents how the various memory systems may be integrated into a multi-memory cognitive architecture. Section 6 reviews a selected collection of experiments and applications of fusion ART models and algorithms. The final section concludes and discusses future work.

2. Fusion ART: Model and dynamics

Fusion ART employs a multi-channel architecture (see Fig. 1), comprising K pattern channels or input fields $F_1^{c1}, \ldots, F_1^{cK}$ connecting to a category field F_2 through bidirectional conditionable pathways. This generalized form of ART model unifies a number of network designs, notably the original single-channel ART models (Carpenter & Grossberg, 1991, 2003), the dual-channel Adaptive Resonance Associative Map (ARAM) (Tan, 1995) and the three-channel Fusion Architecture for Learning, COgnition, and Navigation (FALCON) (Tan, 2004).

By inheriting the ART properties, Fusion ART is naturally designed to learn cognitive nodes, each encoding the multi-modal representation of a memory chunk across multiple pattern channels, in response to a continual stream of incoming patterns in an online and real time manner. However, it is important to note that fusion ART does not require all inputs to be present in the pattern channels. For those channels not receiving input, the input vectors are typically initialized to all '1's, indicating "unknown."

The fusion ART's dynamics is determined by a set of parameters $\mathcal{P}$, consisting of the so called choice parameters $\alpha^{ck} > 0$, learning rate $\beta^{ck} \in [0, 1]$, contribution parameters $\gamma^{ck} \in [0, 1]$ and vigilance $\rho^{ck} \in [0, 1]$ for $k = 1, \ldots, K$. Given a set of selected parameter values, a fusion ART model learns a set of recognition categories in response to an incoming stream of input patterns presented via multiple pattern channels. Specifically, each category node j in the F_2 field thus learns to encode a template pattern $\mathbf{w}_j^{ck}$ representing the key characteristics of a set of patterns presented at each pattern channel ck.

As shown in Fig. 2, upon an input presentation, the fusion ART code learning cycle consists of four key stages, namely code activation, code competition, template matching, and template learning, described as follows.

Code activation: Given a set of input vectors $\mathbf{I}^{c1}, \ldots, \mathbf{I}^{cK}$ presented at $F_1^{c1}, \ldots, F_1^{ck}$ respectively, a bottom up activity propagation process computes an input activation value T_j for each F_2 node j, by

$$T_j = Choice(\{\mathbf{w}_j^{ck}\}|\mathbf{I}^{c1}, \ldots, \mathbf{I}^{cK}). \tag{1}$$

The *Choice* function T_j evaluates the aggregated overall similarity of the input vectors to their respective weight vectors encoded by F_2 node j. The specific similarity function used in the individual pattern fields depends on the types of ART operations chosen, which can be ART1 (Carpenter & Grossberg, 1987b), ART2 (Carpenter & Grossberg, 1987a), ART2-A (Carpenter, Grossberg, & Rosen, 1991b), or fuzzy ART (Carpenter, Grossberg, & Rosen, 1991c) operations.

Code competition: A code competition process follows, which typically results in a winner-take-all outcome. The winner is indexed at J where

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

When a category choice is made at node J, the activity value y_J of the F_2 node J with the highest input activation value becomes '1', while the other F_2 nodes have their activity value y_j set to '0'.

Template matching: Following the code competition process, the chosen F_2 node J performs a reading out of its template weight vectors $\mathbf{w}_J^{ck}$ into the input fields $F_1^{c1}, \ldots, F_1^{ck}$. A *Match* function m_J^{ck} is then computed for each pattern channel ck by

$$m_J^{ck} = Match(\mathbf{I}^{ck}|\mathbf{w}_J^{ck}). \tag{3}$$

The *Match* function is required to ensure that the weight templates of node J are sufficiently close to their respective input patterns before learning. Formally, the state of *resonance* is said to be achieved if for each channel k, the *match* function m_J^{ck} of the chosen node J is at least its corresponding required vigilance value.

If any of the vigilance criteria is not met, mismatch reset occurs in which the node J is reset for the duration of the input presentation. The search process then selects another F_2 node J under the revised vigilance criterion until a resonance is achieved.

Template learning: When the state of *resonance* is achieved, for each channel ck, the weight vector $\mathbf{w}_J^{ck}$ is adjusted to encode the matched patterns in the F_1^{ck} pattern field by

$$\mathbf{w}_J^{ck(new)} = Learn(\mathbf{w}_J^{ck(old)}, \mathbf{I}^{ck}). \tag{4}$$

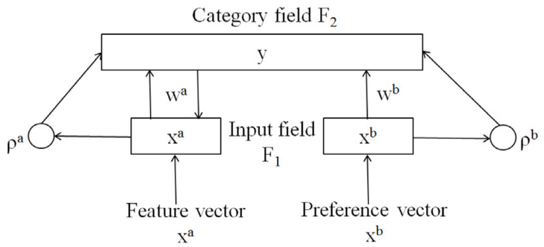

Fig. 3. The architecture of two-channel fusion ART that incorporates user preferences.

Again, the specific *Learn* function used for each pattern channel follows the chosen ART operations used.

When an uncommitted node is selected for learning, it becomes *committed* and a new uncommitted node is added to the F_2 field. Fusion ART thus expands its network architecture dynamically in response to the input patterns.

3. Universal learning

Used in different configurations, the fusion ART network dynamics as described in the previous section are able to support a myriad of distinct learning paradigms.

3.1. From unsupervised to supervised and semi-supervised learning

With a single pattern channel, the fusion ART architecture reduces to the original ART models (Carpenter & Grossberg, 1991, 2003; Grossberg, 1976a, 1976b), which have been applied in the context of unsupervised learning to a wide range of applications.

With two pattern channels, a specific instance of fusion ART known as Adaptive Resonance Associative Map (ARAM), learns supervised associative mappings from one pattern space to another pattern space (Tan, 1995). An ARAM system consists of an input field F_1^a, an output field F_1^b, and a category field F_2. Given a set of feature vectors presented at F_1^a and their corresponding class vectors presented at F_1^b, ARAM learns recognition nodes in the F_2 field that associates key features in the input space to their respective classes in the output space.

In terms of architecture, ARAM can be considered as a compressed version of ARTMAP (Carpenter, Grossberg, & Reynolds, 1991a, Carpenter, Grossberg, Markuzon, Reynolds, & Rosen, 1992) and LAPART (Healy & Smith, 1993), which are extended ART models consisting of two separate ART modules, connected by an inter-ART map field or "Associator."

While the previous section presents a generic code activation process wherein all pattern channels activate the common F_2 field during code activation, for supervised learning, methods such as match tracking can be incorporated into ARAM, which raises the vigilance of the input channel adaptively only when a mismatch occurs in the output channel. This has been shown to reduce the code proliferation problem (Tan, 1995).

In a two-channel fusion ART, it is also possible to perform semi-supervised learning by presenting both labeled and unlabeled samples to the network. Firstly proposed for personalized clustering of search engine results (Tan et al., 2004) and web photos (Meng & Tan, 2012) based on user-defined tags, semi-supervised learning incorporates user-provided category labels to control and refine the clustering results giving more flexibility to the user to enhance the quality of categorization (Meng, Tan, & Wunsch, 2019).

Fig. 3 depicts the architecture of fusion ART that incorporates user preferences for semi-supervised learning. While the F_1^a field receives the features of objects to be categorized, the F_1^b field receives the user preferences for categorizing specific sample objects. Specifically, the preference vector $\mathbf{x}^b$, which encodes the user-defined semantic labeling for the data, is used as a user-guided categorization labeling for the splitting and merging of data clusters.

During learning, the same incremental fusion ART code learning cycle is used to find a cluster in F_2 field that match with both $\mathbf{x}^a$ and $\mathbf{x}^b$ in the F_1 fields. However, the category labeling, in terms of $\mathbf{x}^b$, provides a user-guided control to direct the clustering. It gives more flexibility to the user to direct and adjust the clustering results to be more accurate or fit with the user preferences. This incorporation of user preferences makes fusion ART learning semi-supervised wherein user preferences are taken into account to determine the final clusters. Fig. 4 illustrates the process geometrically as a user-in-the-loop clustering cycle. As illustrated, without the user preferences, fusion ART incrementally clusters the inputs based on predefined distance measures. In contrast, as shown in Fig. 4(b), with the user-specified categorization (e.g the "triangle △", "rectangle □" and "diamond ◊"), the features that were originally partitioned in two separate clusters (in Fig. 4(a)) are united together with the connection of "triangle △", while those originally in the same category can be separated into different clusters.

3.2. Multimodal learning

Fusion ART allows the encoding of multimodal data with an arbitrarily rich level of modalities. To embrace the heterogeneous nature of multimodal data, Generalized Heterogeneous Fusion ART (GHF-ART) (Meng et al., 2014) takes advantage of fusion ART in terms of its linear time complexity and its mechanism that independently processes each feature modality. Specifically, it uses different similarity measure and prototype learning functions for heterogeneous features, and includes a weighting method for feature modalities. GHF-ART has shown promising performance in terms of the social curation of user-tagged web photos (Meng et al., 2014), the detection of user communities in social networks (Meng & Tan, 2014), and the indexing and retrieval of weakly-supervised data (Meng et al., 2015). Essentially, GHF-ART learns the mappings across multi-dimensional feature spaces simultaneously to categories. The clustering process partitions the input feature spaces incrementally to form cluster regions, mapping them to the category space. The clustering procedure of GHF-ART follows the general procedure of fusion ART, namely code activation, code competition, template matching, and template learning. However, it extends fusion ART with an adaptive weighting operation to update the contribution parameter γ^k for every channel k. Formally, the modified *choice* function T_j for node j in F_2 field is given by

$$T_j = \sum_{k=1}^{K} \gamma^k . Choice^k(\mathbf{w}_j^k | \mathbf{I}^{ck}), \tag{5}$$

where the *Choice* function $Choice^k$ evaluates the similarity in input channel k and the contribution parameter γ^k determines the significance of channel k in contributing to the overall *choice* function. Intuitively, a channel that is robustly contribute to the correct categorization should have a high γ^k. To adjust γ^k on-the-fly, a robustness measure R^k for channel k can be obtained by the inverse of averaged differences between the weights and the input values of channel k such that a high R^k indicates that channel k can accurately represent the data that belongs to the same class. In contrast, when R^k approaches zero, it means channel k is less reliable to characterize the input. In that case,

Please cite this article as: A.-H. Tan, B. Subagdja, D. Wang et al., Self-organizing neural networks for universal learning and multimodal memory encoding. Neural Networks (2019), https://doi.org/10.1016/j.neunet.2019.08.020.

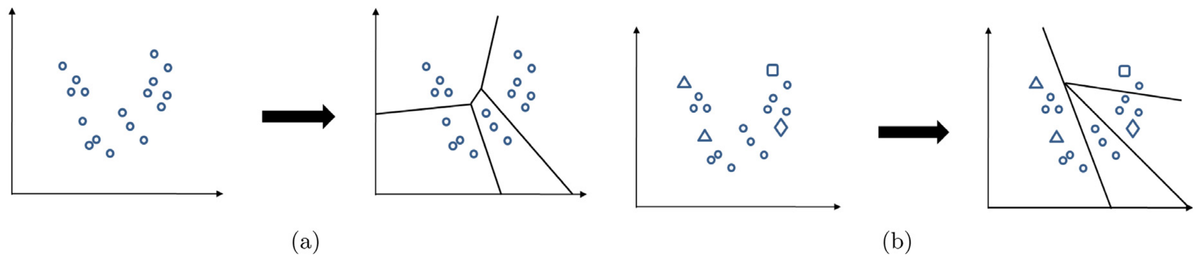

Fig. 4. An example illustrating the influence of user preferences on the clustering results of fusion ART. (a) One possible clustering result of fusion ART — original data shown on the left while the result is on the right; (b) Changes in clustering result after receiving user preferences, i.e. the "triangle △", "rectangle □" and "diamond ◊".

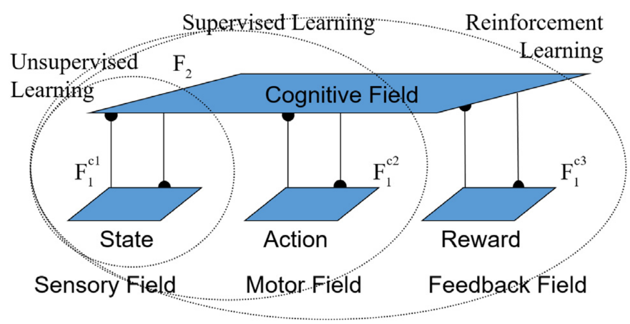

Fig. 5. The FALCON network architecture based on a three-channel fusion ART.

the contribution parameter γ^k can be updated proportional to the robustness R^k by

$$\gamma^k = \frac{R^k}{\sum_{k=1}^{K} R^k}. \tag{6}$$

3.3. Reinforcement learning

Beyond two pattern channels, we show how a specific instant of fusion ART, known as Fusion Architecture for Learning, COgnition, and Navigation (FALCON) (Tan, 2004), subsumes three distinct learning methods, notably unsupervised learning, supervised learning, and reinforcement learning.

The development of FALCON is motivated by designing autonomous agents capable for learning and operating in an embodied real-time environment. As shown in Fig. 5, FALCON employs a three-channel architecture, comprising a category field F_2 and three pattern fields, namely a sensory field F_1^{c1} for representing current states, a motor field F_1^{c2} for representing actions, and a feedback field F_1^{c3} for representing reward values.

When only sensory inputs are presented to the sensory field, FALCON simply reduces to the original ART model performing unsupervised learning of sensory inputs into natural groupings of state representation. When presented with pairings of sensory inputs and actions, FALCON performs supervised learning of associative mapping from the sensory field to the motor field. This is equivalent to learning an action policy directly based on the given supervisory signals. When the reinforcement feedback signals are also presented to the feedback field, FALCON performs reinforcement learning, which learns the value of performing an action in a specific input state. This corresponds to learning a value policy by associating each state–action pair with an evaluative reward value.

A class of FALCON networks, known as TD-FALCON (Tan, 2006), incorporates Temporal Difference (TD) methods to estimate and learn value function $Q(s, a)$, that indicates the merit to take a certain action a in a given state s. The original TD-FALCON algorithm (Tan, Lu, & Dan, 2008) selects an action with the maximal Q-value in a state s by enumerating and evaluating each available action a. A subsequent model called DA-FALCON replaces the action enumeration step with a direct code access procedure (Tan, 2007). Specifically, DA-FALCON searches for the cognitive node which encodes a state similar to the current state and the maximal reward value. It has been shown that if there is at least one cognitive node(s) encoding the current state, DA-FALCON will enable the selection of the cognitive node with the maximum reward value.

To facilitate understanding, the general sense–act–learn cycle for DA-FALCON is summarized below. Given the current state s, TD-FALCON first decides between exploration and exploitation by following an action selection policy. For exploration, a random action is picked. For exploitation, TD-FALCON performs a directed search for cognitive nodes that match with the current states and at the same time provide the highest reward values using a direct access procedure. Upon receiving a feedback from the environment after performing the action, a TD formula is used to compute a new estimate of the Q value of performing the chosen action in the current state. The new Q value is then used as the teaching signal for TD-FALCON to learn the association of the current state and the chosen action to the estimated Q value.

3.4. Sequence learning

As a further extension of fusion ART, iFALCON is a neural model that combines multiple fusion ART networks to emulate the process of planning and plan execution (Subagdja & Tan, 2012). As shown in Fig. 6, iFALCON consists of four input (output) fields F_1^b, F_1^g, F_1^c, and F_1^a, representing beliefs, desires, critic, and action, respectively, which are connected to the category fields F_2 and F_3 representing plans and sequence of actions respectively. In contrast to other fusion ART networks described in the previous sections, iFALCON employs multiple layers of interconnected category fields. The selection output in one category field becomes the input to a higher level one. In iFALCON, the activation pattern in F_3 category field (sequence) becomes the input to the F_2 field (plans), and both F_2 and F_3 become the input fields to the F_4 First-In-Last-Out (FILO) category field. In this multi-layered model of ART, a sequential pattern can be represented as a pattern of node activation in the field (F_3) wherein a value indicates the relative order of time when the corresponding node is selected, stored, and recalled (in First-In-First-Out or FIFO order). Since the sequence pattern is formed only transiently as activation or node selections, the pattern can be stored more permanently as weighted connections representing the gradual pattern of the sequential order. In Fig. 6, the weighted connections from F_3 to F_2 ($\mathbf{w}_j^t$) and to F_4 ($\mathbf{w}_i^s$) represent FIFO sequential pattern.

The beliefs field represents the state of the environment. The desires field represents the goal to be achieved. The critic field evaluates the degree of mismatch between beliefs and desires. The critic value may trigger a resonance search in F_2 or F_4 to

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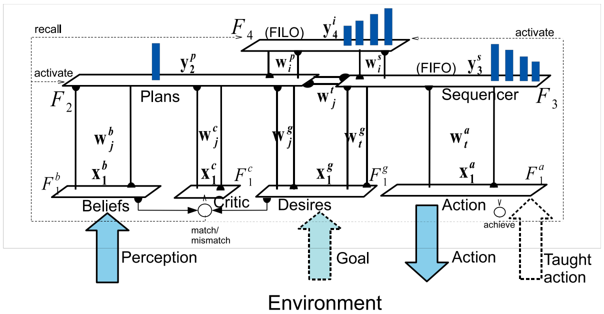

Fig. 6. The iFALCON network architecture based on a hierarchical fusion ART model with four pattern channels.

Table 1
Sample knowledge learned by FALCON in the minefield navigation domain (Tan et al., 2007). The '∧' symbol is used here to indicate the *AND* relation.

Type of learning	Knowledge learned
Unsupervised learning	FrontSonar = 1.0 ∧ Target = Front FrontSonar ≤ 0.5∧ Target = Front
Supervised learning	**IF** FrontSonar ≤ 0.5∧ Target = Front **THEN** Move = Front **IF** FrontSonar = 1.0 ∧ DRightSonar≤0.5 ∧ Target = Front **THEN** Move = DRight
Reinforcement learning	**IF** FrontSonar≤ 0.5∧ Target = Front **THEN** Move = Front (Q = 1.0) **IF** FrontSonar = 1.0 ∧ Target = Front **THEN** Move = Front (Q = 0.0)

select a plan or restore the last condition pending achievements, respectively. The action field represents the action to be taken. As parts of the hierarchical planning system, the achievement of an action in F_1^a may activate a resonance search in F_2 and F_4 to initiate subgoal expansion.

Connected to the four input fields, the F_2 field is the plan repository for storing and recall of plans. Each node j in the F_2 field encodes a plan description, consisting of a pre-condition, a post-condition, a value, and a sequence of actions. Selecting an applicable plan to achieve the goal corresponds to a resonance search to select a node j in F_2 given the goal and the current situation. A new plan will be stored or inserted automatically if the search cannot find any existing match. The F_3 field represents an action controller that stores and replays actions according to their order of presentations. The F_4 field serves as a working memory that stores and reproduces the status of the planning process. Nodes activation in F_4 follows the recency gradient principle (Grossberg, 1978; Grossberg & Pearson, 2008). To restore the status of the plan and action sequence, the F_4 node with the maximal activation is selected for reading out the status of the plan.

In this multi-layered model of fusion ART networks, sequences can be transiently captured and permanently learned by representing the order of node selections as graded activation values. By this sequential encoding technique, a hierarchical structure can also be represented in the networks allowing a reasoning process to be applied for planning and sequential inferences (Subagdja & Tan, 2012, 2015)

3.5. Integrating domain knowledge

During learning, fusion ART formulates recognition categories of input patterns across multiple channels. The knowledge that fusion ART discovers during learning is compatible with symbolic rule-based representation. Specifically, the recognition categories learned by the F_2 category nodes are compatible with a class of conjunctive IF-THEN rules that maps a set of input attributes (antecedents) in one pattern channel to a disjoint set of output attributes (consequents) in another channel. Due to this compatibility, instructions in the form of IF-THEN rules can be readily translated into the recognition categories of a fusion ART system.

The fusion ART rule insertion strategy (Teng, Tan, & Zurada, 2015) is similar to that used in Cascade ARTMAP (Tan, 1997), a generalization of ARTMAP that performs domain knowledge insertion, refinement, and extraction. Cascade ARTMAP follows the ARTMAP network architecture (Carpenter & Grossberg, 1992), consisting of two ART modules ART_a and ART_b connected by an inter-ART associative map field. By representing intermediate variables of rule-based knowledge explicitly and an update mechanism feeding the output activity pattern at the F_1^b field of ART_b module back into the F_1^a field of ART_a, Cascade ARTMAP emulates multi-step inferencing (rule chaining) by performing multiple rounds of code activation for the period of an input presentation. In addition, during learning, new recognition categories (rules) can be created dynamically to cover the deficiency of the domain theory.

For direct knowledge insertion into fusion ART, the IF and THEN clauses of each instruction (rule) are first translated into a pair of vectors **A** and **B** respectively, which are then used as training patterns for inserting into a fusion ART network. During rule insertion, the vigilance parameters of fusion ART are set to 1s to ensure that each distinct rule is encoded by one category node. In addition, existing codes/rules in the network are activated and modified only when they are identical to the inserted rules. Therefore rules learned from data are unlikely to be affected when inserting new rules.

3.6. Explaining learned knowledge

Due to its compatibility with symbolic rules, the knowledge learned by the fusion ART models can also be translated into symbolic IF-THEN rules for interpretation. To illustrate the knowledge learned, Table 1 shows a sample set of the knowledge learned by TD-FALCON in one of our experiments (Tan, Carpenter, & Grossberg, 2007). As shown in the first row of the table, through unsupervised learning, TD-FALCON identifies two key situations in its environment that are of significance. The second row shows two association rules learned by TD-FALCON through supervised learning between typical situations and their corresponding desired actions. Finally, through reinforcement learning, TD-FALCON learns the value of performing a specific action in a given situation. The third row shows two learned cases, one indicating a high payoff for taking an action in a situation and the other giving a severe penalty for taking the same action in a slightly different situation.

4. Neural modeling of memory

It has been well recognized that human brains are multi-memory systems (Kandel, Schwartz, & Jessell, 2000; Tulving, 1985). While declarative memory, in particular episodic memory and semantic memory, is an explicit record of what we encounter and what we learn (Tulving, 1972, 1983), procedural memory refers to skills and reflex responses, which we learn to act in the environment. In this section, we discuss how variants of fusion ART may be used to model the various types of human memory systems, notably episodic memory, semantic memory, and procedural memory.

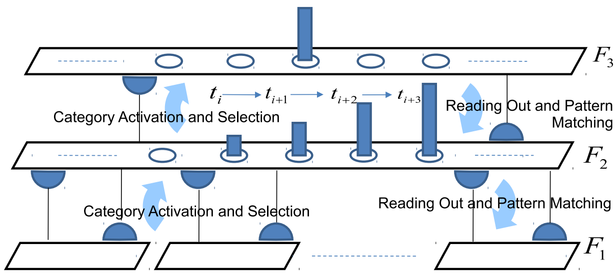

Fig. 7. The EM-ART network model.

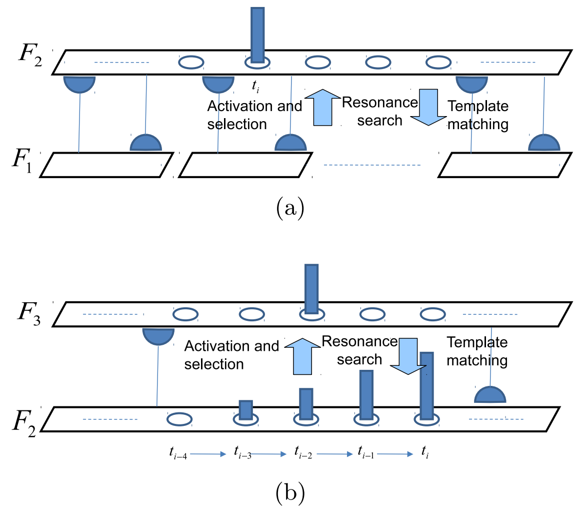

Fig. 8. (a) Event encoding based on network interaction between F_1 and F_2; (b) Episodic encoding based on network interaction between F_2 and F_3.

4.1. Modeling episodic memory

Episodic memory (Tulving, 1983) can be considered as the record of one's life experience, consisting of temporal sequences of events associated with contextual information such as people, objects, times, and places. Two key elements of episodic memory are events and episodes. An event can be represented as an aggregation of attributes describing a snapshot of experience in time. The event attributes characterize the who (subject/object), what (relation/action), where (location), and when (date/time) information of an event. On the other hand, an episode can be defined as a sequence of events, which happen over a period of time.

The main challenge of modeling episodic memory is to build an efficient storage mechanism for encoding an incoming stream of episodic events consisting of multimodal sensory as well as contextual information in real time. The episodic memory should allow generalization across events when required and be scalable and remain plastic (adaptable) to new incoming events. On the other hand, the memory model should enable recall of stored events in real time in response to partial or inexact search cues.

Most early episodic memory models are largely based on symbolic representation (Ho, Dautenhahn, & Nehaniv, 2003; Nuxoll & Laird, 2007; Samsonovich & Ascoli, 2005). Designed to encode complex relationships among the events precisely, they are not able to handle noisy or incomplete cues during memory retrieval. Also, by encoding all incoming events without any form of generalization, the memory storage may have a scaling up issue in a continuous real-time environment.

Building upon fusion ART, the Episodic Memory-Adaptive Resonance Theory (EM-ART) model (Wang, Subagdja, Tan, & Starzyk, 2012a) stores events and episodes by combining two fusion ART networks: one for encoding events and the other for episodes. As shown in Fig. 7, the EM-ART model can be seen as a three-layer fusion ART network consisting of F_1, F_2, and F_3 field.

Event Encoding: The network between F_1 and F_2 is a fusion ART for encoding memory representation of individual events. F_2 serves as a medium-term memory buffer for event activation that holds the graded activity pattern for representing a sequence of events (see Fig. 8(a)). Specifically, an event can be encoded as an input vector to the fusion ART network and a category can be selected as an activated node by a bottom-up activation process. On the other hand, the top-down activation (readout operation) achieves the recall task.

Episodic Encoding: Our approach to encoding a sequence of events in the neural network follows the gradient encoding method (Grossberg, 1978; Grossberg & Pearson, 2008) by maintaining a graded pattern of activities evoked by each incoming event and decayed over time. Fig. 8(b) illustrates the bottom-up and top-down operations between neural fields F_2 and F_3 for learning, recognition, and recalling an episode. Each time when a new event is presented and an event node J is activated, the activation value y_J is set to 1. For all other nodes j in F_2, the activation value y_j is decayed over time by $y_j^{(new)} = y_j^{(old)}(1 - \tau)$ where $\tau \in (0, 1)$ is the decay factor. The activation values y_{t_j} thus form a gradient pattern such that $y_{t_i} > y_{t_{i-1}} > y_{t_{i-2}} > \cdots > y_{t_{i-n}}$, where t_i is the current or the latest time point. The graded activation pattern can then be learned into the weighted connections between the F_2 and F_3 layers.

To retrieve an episode, a continuous search process can be applied, whereby given a stream of incoming event cues, a graded activity pattern of events is accumulated over time in F_2 until a matching node is found in F_3 by the resonance search process. The episodic memory model described above has been shown to robustly retrieve episodic traces using partial and noisy memory cues (Wang, Subagdja, Tan, & Tan, 2012b). An in-depth study on EM-ART as a general cognitive model of episodic memory (Subagdja & Tan, 2015) has provided some proofs that the graded representation of the sequence allows a stored episode to be retrieved even though the memory cues may not be complete (e.g some events missing) and the order of the cue items may slightly be drifted from their original position. In this case, EM-ART offers flexible methods of storing, retrieving, and reasoning over episodic memory that are consistent with memory-related behaviors in humans and animals (Subagdja & Tan, 2015). The flexibility of EM-ART has also been recently demonstrated in controlling task performance of a humanoid robot (Park, Yoo, Kim, & Kim, 2018). Based on a multi-layered (deep) EM-ART network to learn daily routines of activities wherein each layer represents different range of time period of the sequence, the robot can perform a user-instructed sequence of actions properly and completely even though the given instruction is noisy, corrupted, or incomplete (Park et al., 2018). In this case, the instruction is used as a memory cue to retrieve the stored task sequence as episodes.

Whereas the original EM-ART focuses on encoding the sequential aspect of episodic memory, a variant of fusion ART called Spatial–Temporal Episodic Memory (STEM) model (Chang & Tan, 2017) is designed to encode explicit representation of time, space and contextual information of objects, people, and their activities. Using fusion ART as the building block, STEM integrates multimodal episodic memory involving audio, visual imagery, self and other contextual information. As shown in Fig. 9, STEM can be visualized as two fusion ART models connected in a hierarchical manner. The F_1 layer consists of five input fields constituting the event representation, namely the Object field for representing the

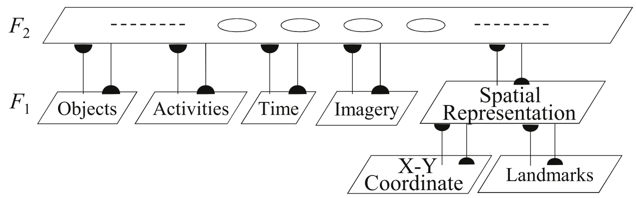

Fig. 9. The STEM network architecture.

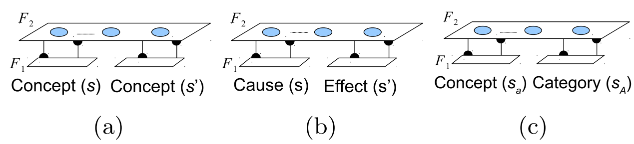

Fig. 10. Three main types of semantic memory, namely (a) association rule ($\mathbf{s}, \mathbf{s}'$); (b) concept hierarchy $\mathbf{s_a} : \mathbf{s_A}$; and (c) causal relation $\mathbf{s} \rightarrow \mathbf{s}'$ encoded by two-channel fusion ART networks.

presence of specific objects in the event, such as "people" and "bag"; the Activity field for representing the presence of specific activity in the event; the Time field for representing the time of occurrence of the event; the Place field for representing the location information of the event; the Imagery field for representing a visual snapshot of the event.

Noted that the STEM model uses the activity values of the nodes in the Time field to encode the time information directly. Besides allowing an explicit representation of time information, similarity matching in time can be supported. As an illustration, the model is designed to encode memories such as "*I went to school yesterday at 9am in the morning*", which can be activated and recalled by a query on "*what did you do yesterday at 8:30am?*." The encoding and recall capabilities of the model have been applied to encoding event-related information extracted from a public domain video data set. Our experiments show that the STEM model is able to support robust recall of the stored events in response to incomplete and noisy search cues.

4.2. Modeling semantic memory

Different from episodic memory, semantic memory stores general meanings, concepts, rules, and facts typically acquired over a possibly long period of time rather than specific experienced events. Over the past decades, various types of structure and representation have been proposed for semantic memory. To aid discussion, a mathematical formulation for representing three common types of semantic memory is presented below.

Semantic Memory, denoted by $S = \{S_1, S_2, \ldots\}$, can be viewed as a set of semantic fragments or codes. Each semantic code S_i, can be one of the three basic types described as follows: (1) an association rule indicates the co-occurrence of two memory states, each representing any piece of information or concept stored. Each association rule is represented as $S_i = (s, s')$, where s and s' indicate the two associated objects or concepts. For example, "People who buy milk usually buy some bread together."; (2) a rule of concept hierarchy defines the "IS-A" relation between two known concepts and can be represented by $S_i = (s_a, s_A)$, wherein s_a and s_A refer to the memory representation of the concept a and its category A respectively. For example, "Pigeon is a kind of bird."; and (3) a causal relation rule states the causality between two memory states and is written as $S_i : s \rightarrow s'$, wherein s refers to the cause and s' represents the effect. For example, "Eating crabs with some fruits usually causes diarrhoea and vomiting."

As shown in Fig. 10, all three types of the semantic knowledge structures may be represented using a two-channel fusion ART model. Specifically, each semantic rule is encoded as a category node in the F_2 layer of the corresponding fusion ART network. The representation of each concept in the rule is specified by the weights between the category node and the two input fields.

4.3. Modeling procedural memory

Procedural memory is a class of human memory systems that involves reactive action or decision making in response to specific situations presented by the environment. It can be realized via a collection of action rules, each of which encodes a state–action pairing to perform familiar routines or well-rehearsed tasks. More formally, a mathematical formulation for procedural memory can be defined as follows.

Procedural Memory, denoted by $P = \{P_1, P_2, \ldots\}$, is a set of action rules which perform the learned tasks and routines. Each action rule P_k suggests a possible action a with an expected reward r (payoff), based on a given situation s. Therefore, each action rule can be represented as $P_k : s \rightarrow (a, r)$. Typically through reinforcement learning, procedural memory learns the association of the current state and the chosen action to the estimated reward.

Similar to semantic memory, a simple form of procedural memory can be learned by a three-channel fusion ART, known as FALCON, via reinforcement learning. As presented in Section 3, FALCON employs fusion ART dynamics for learning the value functions estimated by the temporal difference learning rules. Upon learning, each F_2 category node in FALCON corresponds to a procedural memory code linking a state s to an action a with an estimated reward r.

5. An integrated multi-memory cognitive architecture

To illustrate how the various memory systems may work together, this section presents a minimalist cognitive model with an explicit modeling of episodic memory, semantic memory, and procedural memory. As shown in Fig. 11, the overall architecture comprises five main components, described as follows.

- **Executive Control** maintains a set of goals in hand to regulate the decision making process linking sensory input to motor responses.
- **Working Memory** is a medium-term memory buffer that maintains the mental status at the point in time. In a neural architecture, working memory may be implemented as a field of neurons of which the activity values reflect the inputs from the sensory field as well as the accumulated inferenced results from the memory modules. The working memory is a "medium-term" memory in the sense that the activated neurons stayed activated during a decision making session. It may further interact with an attention mechanism to ensure that only the information relevant to the current task is retained in the working memory.
- **Episodic Memory** encodes past experiences in the form of events and episodes. These memories can be acquired by an EM-ART model, consisting of two layers of fusion ART, via unsupervised learning.
- **Semantic Memory** encodes various forms of semantic knowledge, which can be concept hierarchy, causal relations or association rules. This knowledge can be learned by two or three-channel fusion ART models via supervised learning.
- **Procedural Memory** encodes action rules, each of which is a pairing of a situation to an action. The procedural knowledge as mentioned is learned via a three-channel fusion ART, also known as FALCON, via reinforcement learning.

Please cite this article as: A.-H. Tan, B. Subagdja, D. Wang et al., Self-organizing neural networks for universal learning and multimodal memory encoding. Neural Networks (2019), https://doi.org/10.1016/j.neunet.2019.08.020.

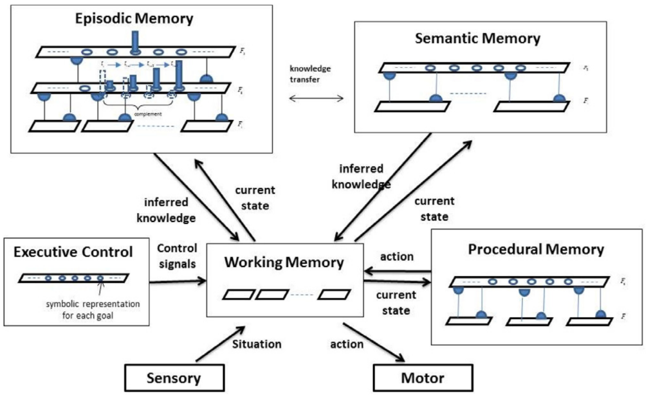

Fig. 11. The overall architecture of the multi-memory cognitive model.

In this architecture, each of the memory modules is designed to support its own operations for the encoding, learning, and retrieval of memory. However, the overall decision process and functions of the system are a result of the dynamic interactions among the various memory modules. Although ART models, in their most original neural implementation, are designed to operate in a self-organized manner based on dynamic differential equations integrating activity values from multiple sources, the stability in individual modules is achieved by the code competition and top-down matching process before any learning takes place in a state of resonance. To enforce stability at the system level, high level goal-driven functions or decision cycles, consisting of definitive stages such as *sense*, *reason*, *act*, and *learn*, may be imposed to direct the operations of the various memory models. In the following sections, we discuss how the episodic, semantic, and procedural memory modules are able to interact via the working memory for the functions of memory consolidation and decision making.

5.1. Episodic to semantic memory consolidation

During memory consolidation, selected content of episodic memory is read out into the working memory, which in turn triggers the learning process in semantic memory (Wang et al., 2012a). As each event is presented, it is evaluated for whether it describes an instance relevant to a type of semantic rules of interests. A type of semantic rules is said to be "of interest" if such rules are deemed important and to be learned by the semantic memory. For example, the semantic memory in Fig. 12 is designed to learn semantic rules on object–location map, weapon effectiveness, and causal relations. An event is relevant to a type of semantic rules of interest, if it contains the input and output attributes for learning such semantic rules. If so, the event representation held in the working memory is forwarded to the semantic memory for learning. Otherwise, the memory playback continues on to the next stored event.

As illustrated in Fig. 12, various types of domain specific semantic memories, such as correlation between objects and locations in the environment, weapon effectiveness with respect to the distance of the opponents, and causal relations between events, can be learned through the playback of episodic memory in the working memory buffer.

5.2. Semantic and procedural memory interaction

As discussed above, while procedural memory is responsible for action selection and reinforcement learning, its behavior may be influenced by the interaction with the other memory modules.

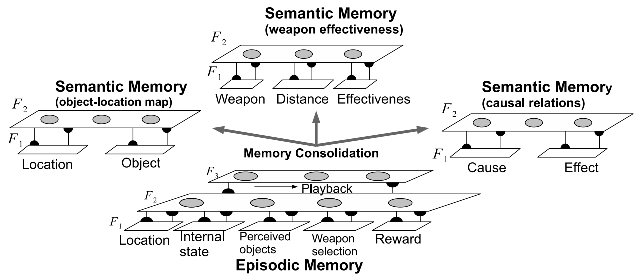

Fig. 12. Illustration of how various types of semantic memory may be learned through a consolidation process from episodic memory.

Specifically, given the current state of the working memory, the action to be executed is selected through the procedural memory. However, during the process of online decision making, the agent may discover the solutions to novel situations based on the knowledge provided by semantic memory. For illustration purpose, we discuss two basic types of interaction between the semantic and procedural memory below.

5.2.1. Semantic to procedural (SP) interaction

In this basic form of interaction, semantic memory is used to provide the contextual information for activating relevant action rules in the procedural memory. More formally, given the current state s, a semantic code $S_i : s \rightarrow s'$ *or* $S_i = (s, s')$ and a procedural code $P_k : s' \rightarrow (a, r)$, where r represents a good reward, the state s can trigger an action a leading to a good outcome according to the procedural rule P_k.

Upon SP interaction, if the procedural rule leads to a favorable outcome, the procedural memory may learn to directly associate the memory state s with the action a, which can be expressed as: $P_{new} : s \rightarrow (a, r)$.

5.2.2. Procedural to semantic (PS) interaction

In order to make a decision, procedural memory may trigger a search in the semantic memory for the missing information for firing a specific action rule.

More formally, given the current state s and a procedural rule $P_k : s' \rightarrow (a, r)$, the semantic memory is primed to search for a semantic code of the form $S_i : s \rightarrow s'$ *or* $S_i = (s, s')$, which will lead the current state s to s'. If S_i is found, the procedural rule P_k is fired.

Again, if the selected procedural code leads to a favorable outcome r, the procedural memory may learn to directly associate the memory state of s with the action a as $P_{new} : s \rightarrow (a, r)$.

6. Experiments and applications

The various models and algorithms described in this paper have been evaluated through empirical experiments and applied to a wide range of applications. This section illustrates how the fusion ART models are used in selected application domains, including modeling autonomous non-player characters (NPCs) in real-time computer games, development of multimodal search engine, simulating computer generated forces (CGF), and neurocognitive study of autobiographical memory.

6.1. Modeling NPCs in First-Person games

Games are excellent test-beds to evaluate AI methodologies. In this section, we show how fusion ART may be used to build Non-Player Characters (NPCs) in a well-known First-Person Shooter

Please cite this article as: A.-H. Tan, B. Subagdja, D. Wang et al., Self-organizing neural networks for universal learning and multimodal memory encoding. Neural Networks (2019), https://doi.org/10.1016/j.neunet.2019.08.020.

Fig. 13. A screenshot of the Unreal Tournament game, wherein FALCONBot (bottom) is engaging fire with advancedBot. The internal and environmental inputs to the state space of FALCONBot include its health level, damage status, amount of damage inflicted to opponent, ammunition available (bottom), and health kits available (top) etc.

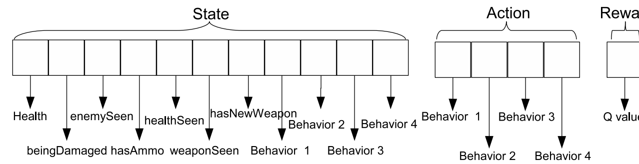

Fig. 14. Vectors used to model the behaviors of FALCONBot.

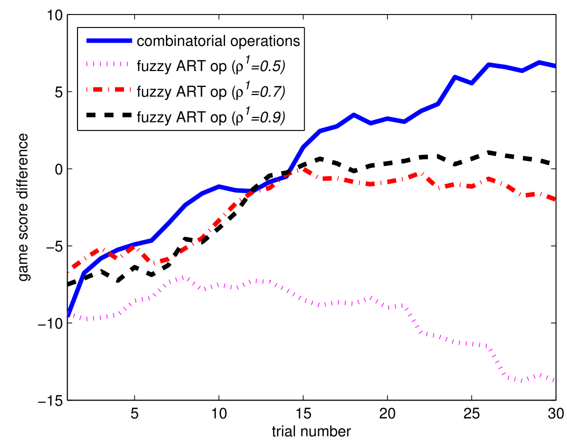

Fig. 15. Averaged game score difference between FALCONBot in difference configurations and advancedBot.

(FPS) computer game named Unreal Tournament (UT). Specifically, we design and implement autonomous agents (interchangeably called NPCs or bots) to play 1-on-1 "DeathMatch" games in UT (see Fig. 13). The game objective is to kill as many opponents as possible and avoid being killed at the same time. For a better chance of winning, the NPCs are required to effectively navigate the 3-D game environment and collect useful items, such as health kits, weapons and ammunition.

6.1.1. Procedural memory for behavior learning and weapon selection

To enable our NPCs to learn autonomously in real-time based on the inputs perceived in the game environment, we employ TD-FALCON networks (see Section 3) to model their behaviors. Specifically, we define an action space, consisting of four alternative behavioral modes for our agents, described as follows:

1. Run around mode, wherein the agent explores the game environment by moving to a randomly selected, reachable location.
2. Item collection mode, wherein the agent marches to a particular location to pick up a collectible item placed there.
3. Escape from battle mode, wherein the agent flees the battle field and collects health kits (if any) along the way.
4. Engage fire mode, wherein the agent fires its weapon at its opponent while avoids getting hit. Upon switching to this mode, the agent may change its weapon in use based on the circumstances.

We implement a TD-FALCON network using the state space shown in Fig. 14 to model the behaviors of our agent named FALCONBot (Wang & Tan, 2015a). The state, action and reward vectors are used as the respective inputs to the TD-FALCON network (see Fig. 5). The state vector captures information about the status of FALCONBot, such as "health", "beingDamaged", "hasAmmo" and "hasNewWeapon", situation about the surrounding, such as "enemySeen", "healthSeen" and "weaponSeen", and its current behavior state. The cardinality of the action vector always equals 1, because at any time, FALCONBot should be in one and only one of the four behavior states. The reward value is estimated using Q-learning. Moreover, besides receiving a direct reward of 1 when FALCONBot kills an opponent and 0 when it gets killed, FALCONBot also receives an immediate reward of 0.75 when it hits the opponent, increases health, or collects new weapon.

The partially perceived game information in UT makes learning in this game a Partially-Observable Markov Decision Process (POMDP). For example, the health status of the opponent is not known to FALCONBot. Therefore, the outcome of the same or similar action may vary drastically. To cater for effective learning in POMDP, we proposed combinatorial operations (Wang & Tan, 2015a), which combine the advantages of Fuzzy ART operations (Carpenter et al., 1991c) for knowledge generalization (applied in the State and Action fields) and ART2 operations (Carpenter & Grossberg, 1987a; Carpenter et al., 1991b) for function approximation (applied in the Reward field). To evaluate the effectiveness of the proposed combinatorial operations, we compare the performance of FALCONBot in different configurations when playing against the same opponent named advancedBot provided by the game interface developers. As it performs all the basic high-level tasks and always uses the most primitive weapon, advancedBot is chosen as the baseline comparison bot due to its steady level of performance. Fig. 15 shows the performance comparisons among the different FALCONBot configurations. As shown in Fig. 15, higher vigilance values for the state field (ρ^1, see Template Matching in Section 2) used in fuzzy ART operations produce better results. Specifically, when $\rho^1 = 0.5$, learning fails as the performance keeps dropping after a slight increase in the early game trials. Nonetheless, even when $\rho = 0.9$, the performance of fuzzy ART operations does not improve after the 16th trial and only achieves 1.05 as the highest game score difference. As a comparison, combinatorial operations are able to continually improve the performance till the last five game trials when exploration ceases and achieve the highest game score difference of 6.9 when playing against the same baseline opponent. Therefore, combinatorial operations are shown to perform significantly better than pure fuzzy ART in this POMDP game.

Besides learning behavior modeling knowledge, we further investigate whether FALCONBot can learn the weapon effectiveness in its procedural memory through reinforcement learning

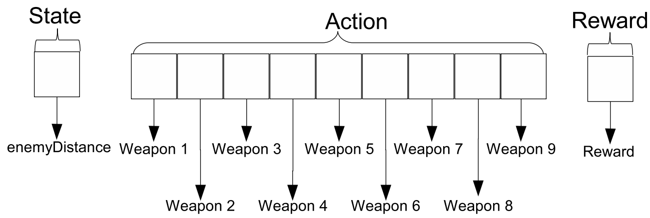

Fig. 16. Vectors used to learn weapon effectiveness.

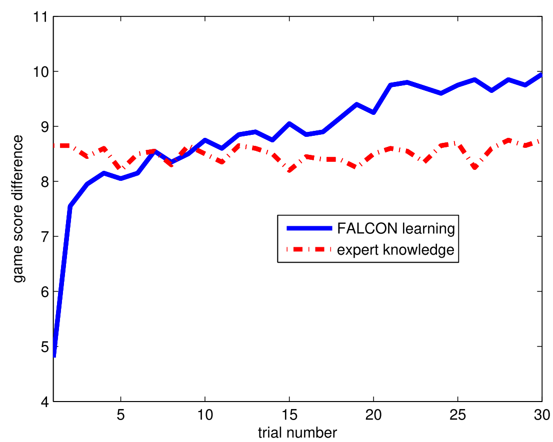

Fig. 17. Averaged game score difference between FALCONBot using different weapon selection strategies and advancedBot.

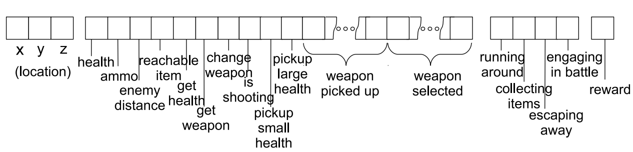

Fig. 18. An example of event encoding in the Unreal Tournament game.

as well. Specifically, we deactivate the weapon selection function calls that utilize heuristic rules provided by game developers, and restrict FALCONBot to rely on a FALCON network for all weapon selection decisions. The information vector used to learn weapon selection knowledge is shown in Fig. 16. In essence, this weapon selection FALCON network learns the associations among the distance (to the opponent), specific weapon, and the corresponding effectiveness. The reward is determined by whether FALCONBot kills its opponent, misses the target, and causes damage. Moreover, in this experiment, we adopt one set of behavior modeling knowledge learned in the previous experiment and disabled the adaptive learning in behavior modeling. As such, we can focus on the assessment of the learned weapon selection knowledge.

Fig. 17 shows the results of FALCONBot playing against advancedBot using self-learned weapon selection knowledge through FALCON and relying on predefined expert knowledge. The results are encouraging that the learned knowledge leads to better performance than expert knowledge.

To illustrate the learned knowledge in FALCON networks, we present two learned behavior modeling rules (translated) in Table 2 and two learned weapon selection rules (translated) in Table 3 (Wang & Tan, 2015a). The values shown in square brackets ([ ]) represent the range of distance in the game. As shown, the translated knowledge is comprehensive and consistent to the domain knowledge in the UT game.

Table 2
Translated example rules for behavior modeling.

IF	Health is around [87, 109], not being damaged, opponent is in sight, has adequate ammo, has health boost nearby, has no weapon nearby, possessing only primitive weapons, and currently in RUN_AROUND state;
THEN	Go into ENGAGE state;
WITH	Reward of 0.729.
IF	Health is around [2, 21], being damaged, opponent is in sight, has adequate ammo, has no health boost nearby, has no weapon nearby, possessing only default weapons, and currently in ENGAGE state;
THEN	Go into ESCAPE state;
WITH	Reward of 0.05.

Table 3
Translated example rules for weapon selection.

IF	Distance is very near [108, 317];
THEN	Use flak cannon;
WITH	Reward of 0.838.
IF	Distance is far [1781, 2364];
THEN	Use lightning gun;
WITH	Reward of 0.781.

6.1.2. Multi-memory modeling for NPC

The use of NPCs in computer games has also been adopted for studying more sophisticated and realistic models of memory. Wang et al. (2012a) use the UT game to study episodic memory (EM-ART) and memory consolidation when the NPCs are performing complex tasks under real-time constraints. As an episodic memory model, EM-ART use the structure for event encoding as shown in Fig. 18. As the NPC moves around the environment and engaging with the opponents, it receives a stream of events wherein each of them is stored consecutively in sequence as episodes (see Fig. 8).

A study has looked at the robustness of episodic memory to retrieve memory items when the cues are noisy or incomplete in the UT environment (Wang et al., 2012a). Compared to Spatio–Temporal LTM (Starzyk & He, 2009), as one of the highly robust sequential learning model that can also deal with noisy cues, EM-ART can still retrieve the correct episodes most of the time (at least 75% of the test items) when 30% noises are introduced to every incoming cue event causing the compared LTM model to get only less than 30% of the correct episodes. When the noises are applied to the sequential order of the cue episodes, EM-ART can still retrieve all the correct memory items completely with 50% level of sequential noises compared to the LTM model that only retrieve less than a quarter of all the target items (20%–25% of the correct items) at the same level of noises. The results show that EM-ART is highly robust in correctly recalling the experiences in roaming the UT environment even though the memory cues are noisy, unordered, or partially corrupted.

Episodes stored in EM-ART are periodically consolidated to a semantic memory, particularly for the knowledge about weapon effectiveness as shown as one of the semantic memory networks in Fig. 12. This is done by playing back the episodes periodically and passing the items retrieved to a working memory system that transiently holds the information. The semantic memory then learns to generalize the information in parallel from this transient buffer while the NPC plays the game (Subagdja, Wang, Tan, Tan, & Teow, 2012). Experiments are also conducted to study the effects of different memory processes like consolidation and forgetting in the game play. For example, to deal with noises from the environment that can make the stored items erroneous and corrupted, some nodes learned may be removed (forgotten) from the network if they are infrequently used or rarely retrieved in order to regulate the memory capacity. However, it is found

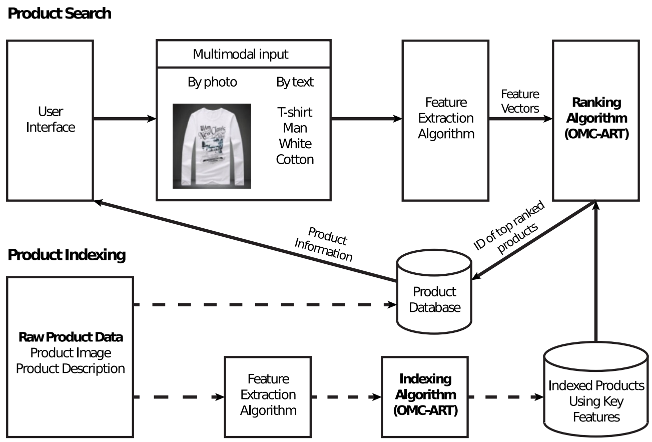

Fig. 19. The process flow of the search engine incorporating OMC-ART. Solid lines correspond to the search process conducted on-line; dashed lines show the off-line indexing processes.

that not only the nodes removal helps to maintain a manageable memory size in the long term, but also enhances the robustness and reliability of memory retrieval in a noisy environment. With 5%–20% noises in the memory cues, more correct episodes (5%–25% more) can be retrieved with the nodes forgetting mechanism than in the one without it (Wang et al., 2012a). This interesting characteristic has also been observed in the UT game wherein the NPC with the multi-memory model can gain more score in playing the 'DeathMatch' game when more under-utilized nodes are removed (Subagdja et al., 2012).

6.1.3. Playing StarCraft strategic game

Beyond First-Person-Shooting (FPS) game, fusion ART with the multi-memory model has also been applied to play a real-time strategic game named StarCraft™. In StarCraft™, a player has a multitude of interrelated game objectives and tasks to accomplish like collecting natural resources, building construction, unit systems production, and even engaged in a battle situation. In this more complex strategic game, the multi-memory system is employed to play the game to study the characteristics of the multi-memory model in the game (Wang, Tan, & Teow, 2017).

In particular, the model of multiple interacting memory systems as described in Section 5 is applied to play the StarCraft™ game to achieve multiple objectives. Three different kinds of fusion ART memory model are applied: one is the procedural memory that conducts actions according to a value function as in reinforcement learning (e.g FALCON), the second one is a semantic memory to encode causal relations between available resources and possible building construction actions, and the last one is a semantic memory to encode causal relations between available resources and possible unit production actions. In this StarCraft™domain, the semantic to procedural interaction is used together with the procedural to semantic interaction as described in detail in Section 5.

Experiments using the StarCraft™domain have been conducted to investigate whether the interaction between different memory systems can affect the performance of the player in gaining the game score (Wang et al., 2017). Particularly, it is demonstrated that both procedural-to-semantic (PS) and semantic-to-procedural (SP) interactions enable the player to gain much higher score than the procedural memory system (PR) alone consistently for three different types of scoring criteria (resource gaining score, construction score, and unit production score). The least score differences between the interacting model and the standalone PR are in the resource collection configuration where PR can gain around normalized score 0.4 and both PS and SP around 0.65. On the other hand, the most significant differences occur in the unit production score configuration where the PR alone configuration achieves only 0.1 normalized score when both SP and PS interactions gain more than 0.9. Overall, it is demonstrated that the memory system performs significantly better in accomplishing different tasks when different memory systems interact together rather than when they are used independently (Wang et al., 2017).

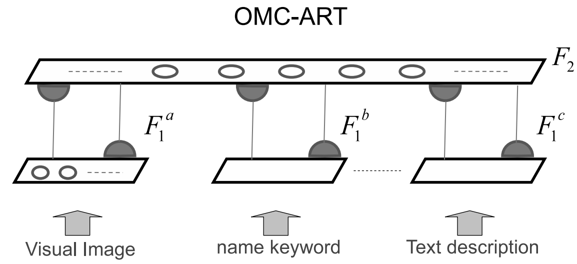

Fig. 20. The OMC-ART architecture for healthcare product search engine.

6.2. Multimodal product search

Nowadays, search engines have been an essential tool in people's daily lives. The current challenges in making a good search engine, particularly for finding e-commerce products, include dealing with big ever-changing data that continuously being updated and the diversity of the users' preferences and background knowledge. Motivated by the issues, OMC-ART, as an extension of fusion ART, has been applied as an on-line indexing and search engine for multi-modal e-commerce product data.

Fig. 19 shows the overall process of the search engine comprising OMC-ART (Meng et al., 2015) that includes modules for processing the queries and presenting the results interactively to the user. It also includes an off-line indexing system for e-commerce product data in the background.

Specifically, OMC-ART is a multi-channel fusion ART based on GHF-ART (Meng et al., 2014) for multi-modal learning (see Section 3.2). As a multimodal fusion ART, the network can learn not just the categorization or clusters of the input patterns but also the right values for the contribution parameters during the learning. In other words, the learning algorithm of OMC-ART also determines which channels should be more important than the others. As a multimodal search engine, the user can query the system with OMC-ART using different modalities or types of input data like image, keywords, numbers, other media, or a combination of them.

As a part of the NTU-UBC Research Center of Excellence in Active Living for the Elderly (LILY) "Silver Silk Road" project,[1] a search engine website for e-commerce product was developed that includes OMC-ART. As shown in Fig. 20, the multi-modal data in OMC-ART associated with each product includes one product visual image (consisting of wavelet texture of the image data, grid color moment, and edge direction histogram), a name keyword, and a textual description.

Using E-commerce product data from Amazon™, the search results were evaluated based on the different modalities of query to retrieve the product information. As shown in Fig. 21(a), when an image data of the product is provided to an OMC-ART channel without the keyword or name, it will return the products with similar pictures, but some of them are irrelevant (e.g protein

1 http://www.ntulily.org/silver-silk-road/.

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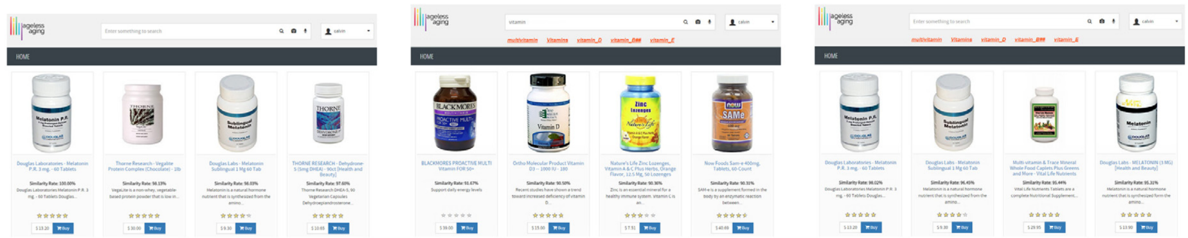

(a) (b) (c)

Fig. 21. The results of search with OMC-ART based on different types of queries: (a) photo image of the product only, (b) name keywords, and (c) both the image and some inexact description.

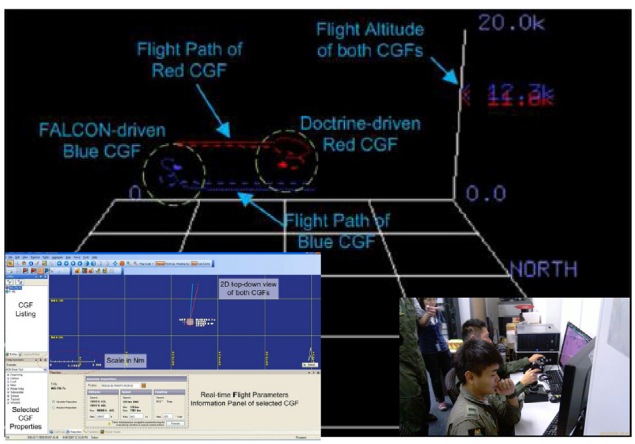

Fig. 22. Strive-CGF™ Air combat maneuver simulation that includes autonomous CGF agents (adapted from Teng et al., 2013). Each CGF agent observes the environment based on relative parameters (e.g orientation, bearing), entity ACM parameters (e.g flight status, maneuver id), and entity parameters (e.g altitude, airspeed, energy ratio). The agent can also perform different maneuver actions including one neutral, three offensive, and nine defensive maneuvers.

pills). When the name keyword only is provided as the query without the picture (e.g "vitamin"), Fig. 21(b) shows that all products retrieved are correct categorically. Although this can be due to a high self-adapted contribution parameter of the name channel as the user frequently interacts with the system, the problem remains when the user does not know the exact name or keyword for the product. In OMC-ART, the user may provide additional inexact textual description in the query besides the picture of the product to improve the search results semantically (e.g all vitamin pills in white bottles) as in Fig. 21(c). This demonstrates that multi-modal queries using multi-modal fusion ART can represent the semantic of the user preferences better even though the queries are inexact.

6.3. Modeling computer generated forces in air combat simulation

Developing a realistic combat simulation for computer generated forces (CGF) requires tedious efforts and costly especially when it involves translating manually crafted military doctrines. Basically, the doctrines refer to domain specific knowledge for performing particular tasks. Specifying the complete rules of engagement and behavior to direct autonomous entities in simulation is less scalable and impractical. It is proposed in Teng et al. (2013) that fusion ART can be applied to support the development of a real-time combat simulation for CGF by allowing new doctrines to be discovered.

Specifically, fusion ART is applied as a reinforcement learning model (see TD-FALCON in Section 3.3) for autonomous CGF entities that perform in CAE Inc.'s Strive-CGF™ air combat maneuver simulation. Fig. 22 shows the screenshots of the simulation display and its context of use. In the simulation platform, a human pilot trainee may engage in a "dogfight" with another human pilot or a virtual one as an autonomous CGF agent. The simulation can be used to analyze air combat strategies or doctrines by observing two or more CGF agents engaged in a combat situation.

Designed to encode knowledge as individual nodes in the neural network, the advantage of using fusion ART in this CGF system can be twofold: initial doctrines or rules can be directly pre-inserted to guide the behavior of CGF agents and additional knowledge learned through reinforcement learning from the battle engagement can be directly extracted from the growing nodes in the network for further analysis and application (see the explainable learned knowledge in Section 3.6).

As a TD-FALCON network (see Section 3.3), the particular fusion ART for CGF encodes the state space and action space as described in Fig. 22 into their corresponding vector representation in the state and action channels, respectively. A reward function is employed for a CGF agent based on whether it successfully eliminates the opponent (high or positive reward) or is eliminated (low or negative reward) by the opponent. Based on the state, action, and reward representation, the reinforcement learning algorithm in TD-FALCON is applied. A combat maneuver doctrine can be inserted directly to the fusion ART network by adding a node in the category field with weight connections reflecting the pattern as expressed in the corresponding vectors representation of state and action space. The corresponding reward channel is set to the maximum value (e.g. 1) to ensure the doctrine is always selected or prioritized whenever the state channel matches with the input.

Special care has been taken, however, in dealing with the inserted knowledge since the normal exploration strategy like ϵ-decay policy in reinforcement learning cannot be applied. Exploring the environment randomly during learning may likely erode the pre-inserted knowledge as experiences resulting in an inconsistent result with the knowledge may change the initial doctrine such that it may make it irrelevant and useless. In that case, the *self-regulating action exploration* strategy is applied based on the average successful attempts ϕ in the current learning episode such that the ϵ parameter is updated based on $\epsilon \leftarrow 1 - \phi$. In that case, the inserted doctrines may only be modified if they produce low performance behavior. When the agent is performing well enough, it is more likely that the doctrine is used more often to direct the behavior rather than just a random exploration.

Experiments are conducted to evaluate the learning capability of the fusion-ART-based CGFs. A non-adaptive CGF agent is built with a set of initial doctrine to start with to engage in a "1-v-1 dogfight" with the adaptive fusion-ART CGF agent (Teng, Tan, Tan, & Yeo, 2012). The adaptive CGF agent is pre-inserted with the same prior doctrine as the non-adaptive one. During the first few iterations (about ten iterations) the learning CGF agent is

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Table 4
Operations applied in AM-ART to realize the three stages of generative autobiographical memory retrieval.

#	Stage	Description given in Conway and Pleydell-Pearce (2000)	AM-ART operations
1	Elaboration	"The elaboration of a cue with which to search memory and the simultaneous setting of verification criteria."	Template masking, mutation (Wang, Tan, & Miao, 2016), and setting of vigilance parameters
2	Strategic search	"Matching the description to records in memory."	Code activation and code competition
3	Evaluation	"Records accessed in memory were assessed against the verification criteria."	Template matching

observed to be struggling to survive as the non-adaptive one effectively uses the pre-given doctrine to eliminate the opponent. Over time, the adaptive agent learn to outmaneuver and eliminate the opponent so that it can gradually overtake the opponent's score. After over 100 iterations, the adaptive CGF agent can consistently eliminate the non-adaptive one most of the time. The experiments demonstrate that the fusion-ART can learn to use and further improve the pre-given doctrines effectively (Teng et al., 2012).

6.4. *Neurocognitive study of autobiographical memory*

As presented in Section 4, fusion ART has been used for modeling various types of human memory systems. In this section, we present a study on using a three-layer fusion ART model named Autobiographical Memory-Adaptive Resonance Theory (AM-ART) network for modeling autobiographical memory formation and forgetting (memory loss).

Autobiographical memory (AM) is a class of memory that encodes, stores and guides retrieval of episodic information related to our personal experiences (Bluck & Levine, 1998). It may be considered as a special form of episodic memory with the associated context and personal emotions. By comparing a widely accepted AM hierarchy established by psychologists (Conway & Pleydell-Pearce, 2000) (shown in Fig. 23) and the network architecture of AM-ART (shown in Fig. 24), it is clear that their network topological structures are highly consistent. For example, the life experience of "working at A" can be represented as a code (learned episode) in F_3 of AM-ART. The associated events of that episode, namely "first day at work", "working in the C office", and "drinks at W Friday evenings" can be represented as codes (learned events) in F_2. A specific event, taking "drinks at W Friday evenings" as an example, can be read out in F_1 (encodes 5W1H, a comprehensive set of event specific information) that on Friday night (time-when), at W (location-where), with colleagues (people-who), drinking (activity-what), feeling happy (emotion-how), together with the pictorial memory (imagery-which). According to the Hippocampal Indexing Theory (Teyler & DiScenna, 1986), the hippocampus provides indices to the associated activities stored. The F_1 fields in AM-ART thus can be considered as representing activities in other brain regions.

Other than the consistent network topology, the memory retrieval process in AM-ART exactly replicates the three stages of the generative memory retrieval presented in Conway and Pleydell-Pearce (2000). These three stages and the corresponding operations applied in AM-ART are summarized in Table 4.

To evaluate the various functions of AM-ART in modeling autobiographical memory, we collected a memory set of Mr. Obama, the 44th president of USA, from public domains. The memory set comprises 1,019 snapshots of life events in 131 episodes spanning across different life period of Mr. Obama. Subsequently, we show that AM-ART is able to efficiently encode all the memories and more importantly, retrieve them using exact, partial and noisy cues (Wang et al., 2016). Specifically, the memory retrieval performance of AM-ART using noisy cues is significantly better than the other models, such as the keyword-based query, which is used by many existing photo or memory repositories.

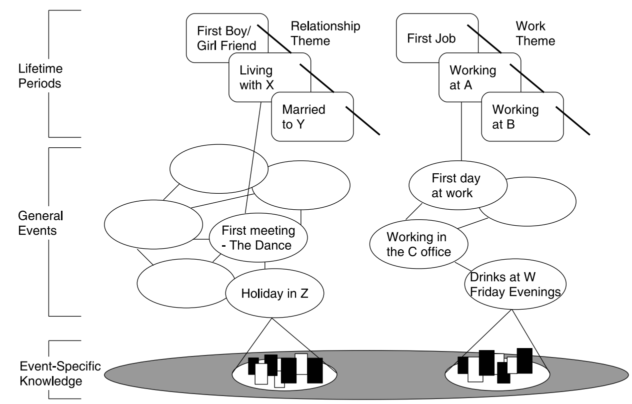

Fig. 23. Autobiographical memory hierarchy.
Source: Adapted from Conway and Pleydell-Pearce (2000).

Moreover, by introducing the mutation operation in AM-ART (Wang et al., 2016), we are able to emulate the wandering in reminiscence memory recall patterns, wherein seemingly random, but contextually connected memories across different episodes of life events are sequentially retrieved. This wandering in reminiscence function is particularly beneficial as a form of cognitive stimuli to improve one's, especially an elder's, cognitive well-being. The corresponding application is presented in Wang and Tan (2015b).

To study how people generally lose their memories and emulate various memory loss phenomena, we further extended AM-ART by introducing the overload, decay and inhibition parameters to replicate memory loss during the memory formation, storage and retrieval stages, respectively (Wang, Tan, Miao, & Moustafa, 2019). Fig. 25 shows the high consistency between the human memory recall performance and that emulated by AM-ART. The averaged correlation between the two subfigures is computed as 0.793 ± 0.166. The capability of computationally modeling memory loss presents an appropriate framework to provide insight into human behavioral processes in a rapid and quantitative manner.

7. Conclusion

This paper has presented a family of self-organizing neural networks, collectively known as fusion Adaptive Resonance Theory (fusion ART), that learns associative mappings across multimodal pattern channels, in an online and incremental manner. As a natural extension of the Adaptive Resonance Theory (ART)

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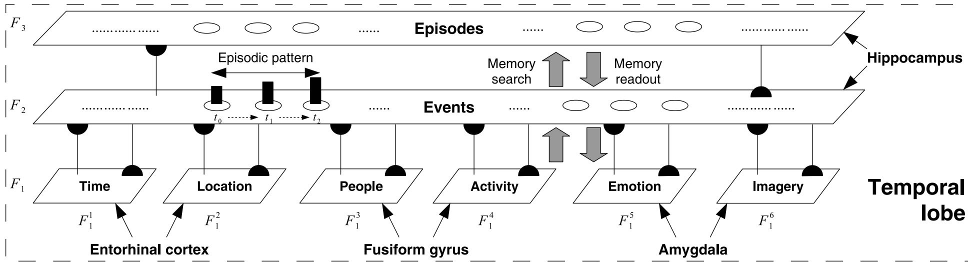

Fig. 24. Network architecture of AM-ART. All its channels and layers match specific brain regions.

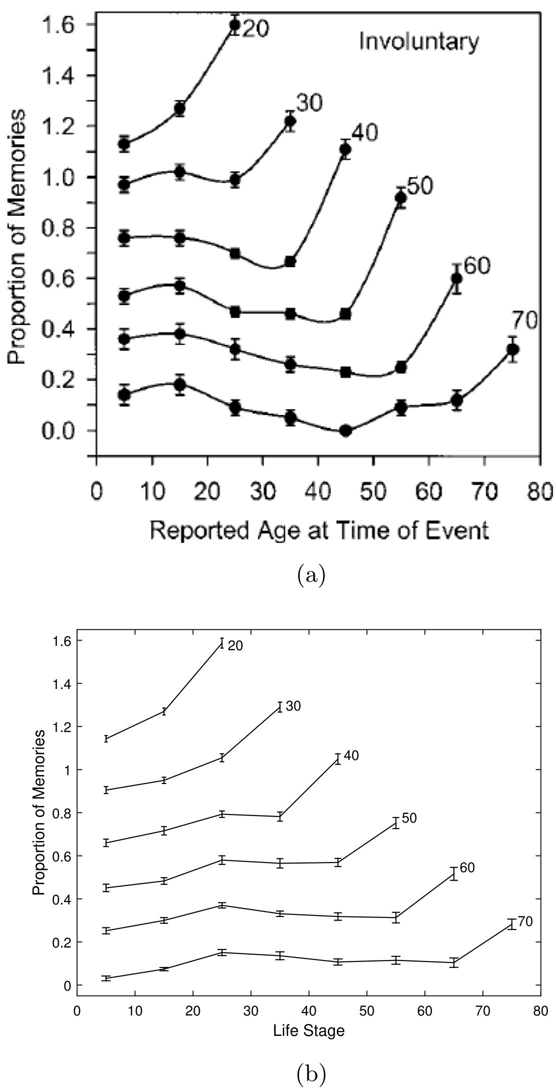

Fig. 25. Memory recall distributions of different age groups across life span: (a) Fig. 6 excerpted from Berntsen and Rubin (2002). (b) Results of AM-ART emulations. To make all plots visible, an offset of 0.2 is applied to each adjacent age group.

model, fusion ART can be adopted for use in a myriad of traditionally distinct learning paradigms, namely unsupervised learning, supervised learning, semi-supervised learning, multimodal learning, sequence learning, and reinforcement learning. In addition, fusion ART models have been used for representing a variety of memory structures, notably episodic memory, semantic memory, and procedural memory. While it is not possible to present the details of the models and experimental results in this paper, it is the authors' contention that the various application and case studies presented, spanning autonomous non-player characters (NPCs) modeling, multimodal product search, computer generated forces (CGF) simulation, and neurocognitive studies, have served to illustrate the efficacy of these neural networks.

As the generic network architecture and computational principles of fusion ART are applicable for realizing a broad range of learning and memory functions, a promising future direction going forward will be to integrate such capabilities into a large scale integrated cognitive architecture. Nevertheless, while we see this as a step towards artificial general intelligence (AGI), the holy grail of AI, the first such system will most likely be grounded for a specific target domain.

Also, the current development of fusion ART is limited to shallow network models, consisting of two to four layers of neural fields. It is thus missing the invariant pattern recognition capabilities prevalent in the hotly studied deep learning neural networks. While there has been recent work on deep Adaptive Resonance Theory (Park et al., 2018), the number of levels in the network models presented did not match the typical scale of deep neural networks. As such, it will be interesting to study how computational principles of fusion ART may be generalized to very deep neural networks.

On the other hand, it is also important to note that fusion ART models play a distinctive role from those of deep networks in cognitive systems, being they biological or artificial. While deep learning based multi-layer neural structures are typically found in primary sensory cortices, fusion ART networks may naturally reside at a higher level of the neural pathways, responsible for fusion and binding of the high level sensory and contextual signals produced by the deep learning networks. Therefore, integrating fusion ART models and deep learning neural networks would also be an interesting research area towards building integrated cognitive architectures and systems.

Acknowledgments

The work presented in this paper was supported in part by the Singapore Ministry of Education Academic Research Fund (MOE AcRF Tier-1) (Project Ref. RG130/18(S)), the DSO National Laboratories, Singapore (Project No. DSOCL11258 and DSOCL16006), the National Research Foundation, Prime Minister's Office, Singapore under its IDM Futures Funding Initiative, and the Singapore Ministry of Health under its National Innovation Challenge on Active and Confident Ageing (Project No. MOH/NIC/COG04/2017).

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