A NOVEL STRUCTURE FOR REALIZING GOAL-DIRECTED BEHAVIOR

Cem Yucelgen, Yusuf Kuyumcu, N.Serap Sengor
Electronics and Communication Engineering Department, Istanbul TechnicalUniversity, Maslak, Istanbul, Turkey
yucelgenc@itu.edu.tr, yusufkuyumcu_2311@hotmail.com,sengorn@itu.edu.tr

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Abstract: Intelligent organisms complete goal-directed behaviour by accomplishing a series of cognitive process. Inspired from these cognitive processes, in this work, a novel structure composed of Adaptive Resonance Theory and an Action Selection module is introduced. This novel structure is capable of recognizing task relevant patterns and choosing task relevant actions to complete goal-directed behavior. In order to construct these task relevant choices the parameters of the system are modified by Reinforcement Learning. Thus the proposed structure is capable of modifying its choices and evaluates the outcome of these choices. In order to show the efficiency of the proposed structure word hunting task is solved.

1 INTRODUCTION

To suppress the irrelevant stimuli amongst similar ones, to focus on the task relevant ones and to perceive these and process them to reach a goal requires accomplishment of a series of cognitive processes. A system capable of realizing these processes would be efficient in many intelligent system applications. In this work, an integrated structure composed of Adaptive Resonance Theory (ART) and Action Selection module (AS) is introduced. This novel structure named ART-AS is capable of recognizing the changes in the environment and is able to adapt itself to these changes according to the rewards it obtains for its choices. There are two different adaptation procedures: (i) one corresponding to selective attention where parameters of ART are modified to recognize goal related patterns and (ii) a second adaptation where parameters of AS module are modified to choose task relevant actions. Both of these adaptation procedures are accomplished by Reinforcement Learning (RL).

In most of the applications, the differential equations defining ART (Carpenter, Grossberg, 1987) are not considered. Instead an algorithm using steady state behavior of these equations is utilized (Tan, 2004). Here the overall ART-AS structure is composed of nonlinear dynamical systems and the behavior of each dynamical system is adapted by the parameters governing their steady-state behavior. So, to determine the parameters that are effective in guiding ART's behavior, the solution of the differential equations are considered. Once, the effective parameters are determined and their interpretation are discussed they are used to guide ART. These parameters of ART are modified by reward expectation error and the task related patterns are obtained in the Long Term Memory (LTM). To order the patterns in LTM according to the task is the last step in concluding goal-directed behavior. This ordering of patterns in LTM is accomplished with a set of difference equations realizing action selection. Another dynamical system defines the AS module which is developed considering the neural substrates that are effective in action selection (Sengor, Karabacak, Steinmetz, 2008). In (Sengor et.al., 2008) it has been shown that this dynamical system is capable of selecting task relevant actions in a goal-directed behavior.Thus, in the proposed ART-AS structure while ART part realizes recognition of task relevant patterns, AS part determines the task relevant actions.

A similar work is (Brohan, Gurney, Dudek, 2010), where a hybrid structure is proposed. In their work Self-Organizing Maps (SOM) and RL are incorporated. Their aim is to solve an action selection problem while organizing SOM with selected actions. Here, ART is considered instead of

SOM and the aim is not only to order features according to actions but to show how pattern recognition can be adapted according to a goal. Another similar work is (Tan, 2004), where ART and RL are used together. In FALCON the main concern is to propose machine learning methods, while here efficiency of a system inspired by neural substrates is investigated.

This paper is organized as following: In Section 2, a scheme for the proposed structure is given. The RL mechanism modifying the parameters of ART-AS is explained. Especially, the differential equations defining ART are considered and the effect of parameters ρ, D1, D2 and L on LTM is investigated. In Section 3, word hunting task is solved using the proposed structure.

2 THE PROPOSED STRUCTURE

The overview of the ART-AS structure together with learning process RL is presented in Fig.1.

In ART-AS structure, some parameters of ART are modified by RL to realize selective pattern recognition.

Modification of the parameters depends on the evaluation of features at LTM by the value assignment block. RL part does not dictate ART what to recognize, it just assigns a value to ART's performance. This assigned value is evaluated by δ_{art}. If ART cannot manage to recognize the stimulus correctly it is not rewarded, and parameter δ_{art} changes the vigilance parameter ρ and parameters D_1, D_2 and Lwhich define the effect of neurotransmitter dopamine.

Once, the perception of task related features is completed, in order to conclude the goal-directed behaviour, these features have to be processed according to the task. The second RL component of the proposed structure is responsible for this process. The features in LTM are processed by the RL block on the lower right hand side of the Fig.1. So the environment in this part is composed of the perceived patterns stacked at LTM. The patterns that are chosen by ART are represented as different states in the environment and actor selects an action corresponding to each of these. The selected action is evaluated by RL and the task related actions are chosen. The error in reward expectation δ_{as} modifies a parameter of the dynamical system realizing action selection thus stimulating actor to choose a different action.

In this setup, while ART with the RL mechanism performs selective pattern recognition, AS part orders the unorganized LTM outputs according to the goal by second RL part.

2.1 Realization of ART-AS

Once stimuli in the environment are presented to F1, this triggers the dynamic progression in this layer which is defined by the differential equation in Eq.1. (Carpenter, Grossberg, 1987):

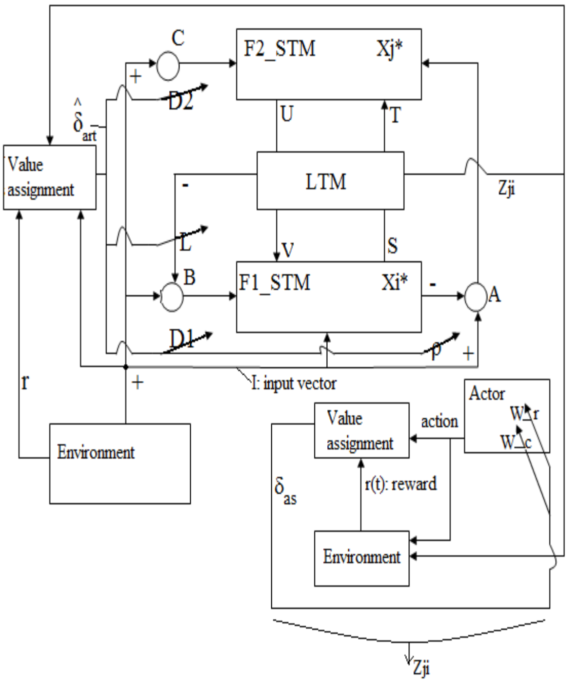


Fig. 1. The proposed structure: The modification of ART and action selection is realized by RL.

$$\varepsilon \frac{d}{dt} x_i = -x_i + (1 - A_1 x_i) J_i^+ - (B_1 + C_1 x_i) J_i^- \qquad (1)$$

Here $J_i^+ = I_i + V_i$ is the excitatory signal. It is equal to $I_{i,}$ as V_i is not formed yet. J_i^- is the inhibitory signal. If vigilance test is not satisfied in gain control unit A, it inhibits the F1 activities. However, in the first step this term does not emerge as features at F1 instead approach to equilibrium point at I_i. Therefore, equation for layer F1becomes

$$\varepsilon \frac{d}{dt} x_i = -x_i + (1 - A_1 x_i)\, I_i\, . \qquad (2)$$

With X_i^* being the solution of Eq. 2, F1 releases signal S to the synaptic field.

$$S = h(X_i^*) = \begin{cases} 1, & X_i^* > 0 \\ 0, & otherwise \end{cases} \qquad (3)$$

Bottom-up activities of LTM are triggered by S.

$$\frac{d}{dt} z_{ij} = K_1 f(x_j)[-E_{ij} z_{ij} + h(x_i)] \qquad (4)$$

At the end of this synaptic process, signal T which stimulates the layer F2 is produced.

$$T_j = D_2 \sum_i h(X_i^*)\, z_{ij} \qquad (5)$$

Dynamic process in layer F2 is defined by Eq. 6.

$$\mathcal{E}\frac{d}{dt}x_j = -x_j + (1 - A_2x_j)J_j^+ - (B_2 + C_2x_j)J_j^- \qquad (6)$$

Similar to layer F1signals $J_j^+ = I_i + T_j$ and J_j^- are the excitatory and inhibitory for layer F2, respectively. J_j^+ is the excitatory signal and starts the activities at F2. On the other hand, depending on the vigilance test result in unit A, J_j^- inhibitory signal is either generated or not generated. When J_j^- is not generated, the equation for F2 becomes as follows:

$$\mathcal{E}\frac{d}{dt}x_j = -x_j + (1 - A_2x_j)(\,I_i + T_j) \qquad (7)$$

With X_j^* being a solution of Eq. 7, F2 releases signal U to synaptic field. This signal is important as it determines the neuron that is effective in recognizing the patterns.

$$U = f(X_j^*) = \begin{cases} 1, & T_j = \max\{T_k\} \\ 0, & otherwise \end{cases} \qquad (8)$$

Top-down synaptic activities is initiated by the signal U and top-down weights start to take shape through Eq. 9.

$$\frac{d}{dt}z_{ji} = K_2 f(X_j^*)[-E_{ji}z_{ji} + h(x_i)] \qquad (9)$$

At the end of this synaptic activity, top-down template V stimulates

$$V_i = D_1 \sum_j f(X_j^*)\, z_{ji}$$

In F1 and unit B, V and I are compared to each other. If result of this comparison exceeds the vigilance parameter ρ, then ART reaches to stable state and forms itself efficiently (Carpenter, Grossberg, 1987). Otherwise, inhibitory signals are produced and signals at layers and synaptic fields are reset. Thus, equations for layer F1 and F2 become

$$\mathcal{E}\frac{d}{dt}x_i = -x_i + (1 - A_1x_i)J_i^+ - (B_1 + C_1x_i)J_i^- \quad (10)$$

$$\mathcal{E}\frac{d}{dt}x_j = -x_j + (1 - A_2x_j)J_j^+ - (B_2 + C_2x_j)J_j^- \quad (11)$$

ART structure is convenient for adaptation and RL mechanism is used to modify the parameters of ART. The performance of ART depends on parameters *ρ, D₁, D₂* and *L*. In (Dranias, Grossberg, Bullock**,** 2000) it is pointed out that, the effect of parameters *D_1, D_2* correspond to the effect of dopamine on cognitive processes. In this work, these parameters are modified by the reward expectation error δ_{art}. The details of this reward mechanism will be explained in detail in (2.2).

Once the patterns formed by ART are stacked at its LTM, these have to be evaluated according to the goal. In order to fulfil the goal, some actions have to be chosen and the patterns have to be processed according to these actions. The dynamical system given in Eq. 12 corresponds to cortico-striato-thalamic loop proposed in (Sengor, et.al., 2008). It is shown that this system is capable of choosing task relevant actions when parameter W_r is modified according to RL.

$$\begin{aligned} p(t+1) &= f(\lambda p(t) + m(t) + W_C I(t)) \\ m(t+1) &= f(p(t) - d(t)) \\ r(t+1) &= W_r\, f(p(t)) \\ n(t+1) &= f(p(t)) \\ d(t+1) &= f(W_d\, n(t) - r(t)) \\ f(x) &= 0.5\,(\tanh(a(x - 0.45)) + 1) \end{aligned} \qquad (12)$$

In (Sengor et.al., 2008) it is discussed that modifying W_r corresponds to modelling the effect of dopamine on action selection. The details of this RL process will be given in Section 2.2.

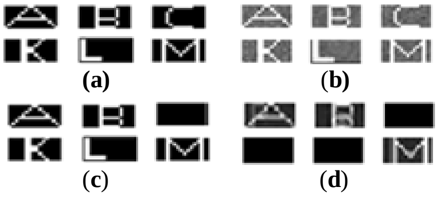
2.2 Learning Process for ART-AS

The solutions of the differential equations governing ART depend on its parameters *ρ, D_1, D_2* and *L*. Any change in these parameters highly affects the behaviour of the nonlinear system. In (Dranias et.al., 2000), it is pointed out that forming the weights to maintain the learning process in LTM relies also on dopamine-gated steepest descent learning. The following two equations are related to the dopamine-gated steepest descent learning:

$$V_i = D_1 \sum_j f(X_j^*)\, z_{ji} \qquad T_j = D_2 \sum_i h(X_i^*)\, z_{ij} \qquad (13)$$

Besides parameters *D_1* and *D_2*, *ρ* has a different role on the system. Following simulation results show this.

As it is depicted in Fig. 2b-c, more features are obtained with higher *ρ* values. Fig. 2b and d manifest the effect of the *D_1* and when *D_1* increases, the number of features formed in the LTM decrease. The effect of *D_2* is not taken into consideration as by itself *D_2* affects only layer F2. However, *D_2* affects LTM when interacts with change in *L*.



(a) (b)

(c) (d)

Fig. 2 Patterns in **(a)** environment (**b)** LTM with *ρ=0.95, D_1=0.2, D_2=0.7, L=1*(**c**) LTM with *ρ=0.55, D_1=0.2, D_2=0.7, L=1*(**d**) LTM with *ρ=0.95, D_1=0.7, D_2=0.7, L=1.*

In (Grossberg, 1999), it is shown that inactivation and releasing of the neurotransmitters for a neuron is based on S in Eq. 14. Using this equation the parameter responsible for neurotransmitter inactivation and release is obtained.

$$\frac{dz}{dt} = A(B-z) - Sz = AB + (-A-S)z \quad (14)$$

Accepting that neurotransmitters release from F1 neurons, and considering z_{ij} in Eq. 9. where E_{ij} is defined as in Eq. 15

$$E_{ij} = h(x_i) + L^{-1}\sum_{k\neq i} h(x_k) \quad (15)$$

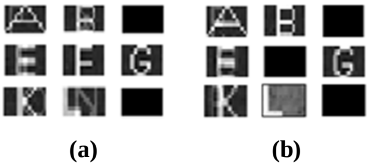
gives the following result

$$\begin{aligned}\frac{d}{dt}z_{ij} &= K_1 f(x_j)(-E_{ij})z_{ij} + K_1 f(x_j)h(x_i)\\ &= K_1 f(x_j)h(x_i) + (-K_1 f(x_j)h(x_i) - \\ &\quad K_1 f(x_j)L^{-1}\sum_{k\neq i} h(x_k))z_{ij} \quad (16)\end{aligned}$$

Considering above equations, S can be obtained in terms of parameter L.

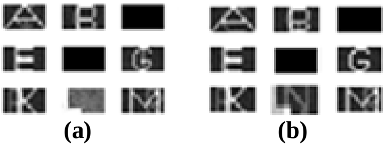
$$S \triangleq K_1 f(x_j)L^{-1}\sum_{k\neq i} h(x_k) \quad (17)$$

Thus, changing the ratio of the inactivation and release of neurotransmitters for one neuron in F1 causes parameter L to have influence on ART. The effect of parameter L can be observed in Fig. 3a where letter “L” is associated with letter “N”. In Fig. 3b this association does not exist. Hence, increasing parameter *L* results in decaying of this association between the patterns in LTM. Also, “F” is not formed with L=30.



(a) (b)

Fig. 3. Patterns in LTM with *ρ=0.95, D_1=0.35, D_2=0.7*
(a) *L=1* (**b**) *L=30*



(a) (b)

Fig. 4. Patterns in LTM with *ρ=0.95, D_1=0.35, L=45*
(a) *D_2=0.7* **(b)** *D_2=0.05*

Fig. 4 shows the influence of D_2; as D_2 decrease, letter “L” is associated with “N” again. However, in this case letter ”G” becomes clear. Also, in Fig. 3 and Fig.4 another effect of *L* can be seen. In Fig.3, “M” does not exist but is formed in Fig. 4.

Considering the results of Fig. 2-4, it can be concluded that while ρ and D_1 are effective on the number of patterns formed in LTM, D_2 and *L* are effective on clarity and formation of some patterns in LTM. These results reveal that ART can be modified with these four parameters. A reward mechanism, similar to one in (Brohan, et.al., 2010) is used and the error δ_{art} modifies the parameters of ART. Owing to the fact that there is no mathematical model introducing the relation between δ_{art}, ρ and D_1, D_2, empirical equations inspired by simulation results are produced. These equations are used to modify the parameters until ART forms the task relevant features. These parameters are controlled by an error parameter $\hat{\delta}_{art}$ obtained in value assignment block. First, in pattern matrices (I) which are composed of “1”’s and “0”’s the elements with value “1” are determined. Then, the elements of LTM outputs corresponding to these elements are determined and $\hat{\delta}_{error\ for\ "1"} = |1 - LTM\ value|$ are calculated for each element corresponding to “1”. These errors are summed up for each input- output pair and smallest value is chosen amongst them. It is named $\hat{\delta}_{art}$. Equations in (18) are determined by $\hat{\delta}_{art}$ which produces δ_{art} according to an emprical formula,

$$\begin{aligned}\delta_{art} &= \frac{\hat{\delta}_{art}}{the\ number\ of\ related\ one\ bit\ places}\\ \rho &= \left|\rho + \frac{\hat{\delta}_{art}}{1-\hat{\delta}_{art}}\right|\\ D_1 &= 0.4\left|D1 - \frac{\hat{\delta}_{art}}{1-\hat{\delta}_{art}}\right| \quad (18)\\ D_2 &= 0.1\left|D2 - \frac{\hat{\delta}_{art}}{1-\hat{\delta}_{art}}\right|\\ L &= 0.3 + 1.3\left|L + \frac{\hat{\delta}_{art}}{1-\hat{\delta}_{art}}\right|\end{aligned}$$

Once a pattern is recognized successfully, in order to perceive other patterns ART’s parameter values are reset to values which give the worst perception of the features. If perception of the new pattern could not be realized with these worst case values, they are updated till they provide better results. When the patterns related to the task are stacked at the LTM, in order to complete the goal-directed behaviour, these patterns are ordered by actions selected with the dynamical system given by Eq. 12. The action selected for a pattern is evaluated by critic. Then the reward *r(t)* and expectation error $\delta_{as}(t)$ are determined as follows (Schultz, Dayan, Montague, 1997).

$$\delta_{as}(t) = r(t) + V(t+1) - V(t) \qquad (19)$$

where the value function $V(t) = (W_v + n(t))I$, $n(t)$ is the noise term and I corresponds to patterns in LTM. This reward expectation error modifies the action selection and value function by updating the W_r, W_v, respectively as follows (Sengor, et.al., 2008):

$$W_v(t+1) = W_v(t) + \eta_v \delta_{as}(t) I'(t) \qquad (20)$$
$$W_r(t+1) = W_r(t) + \eta_r \delta_{as}(t) f(p_{pm}(t)) Er_{pm}(t)$$

To set up the representation of patterns in action selection W_c is updated as

$$W_c\ (t+1) = W_c(k) + \eta_c \delta_{as}(t) p_{pm}(t) I'(t) \qquad (21)$$

3. Simulation Results

In order to verify the effectiveness of the proposed hybrid structure, word hunting puzzle is considered. In the puzzle a set of letters that can form a word should be recognized from a jam of letters. As an example, the template given in Fig.5 is considered.

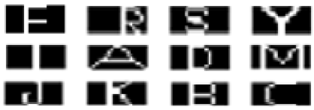


Fig. 5 The word hunting puzzle.

The task is to recognize the letters B,D,I,R and then organize these letters to obtain the word BIRD. An in-house code written in MATLAB® as an m-file is used. For ART, the initial values of weights and x_i, are random positive and negative small numbers. Coefficient matrices, A_1, C_1 and A_2, C_2 are unit matrices which have dimensions same as the input patterns. B_1 and B_2 are column vectors with dimensions same as the patterns and their components are random small positive numbers. All layers' equations are solved out by using Open Euler Method so ε is step size and its value is 0.03. The initial values of parameters are $\rho=0.35$, $L=1$, $D_1=0.75$, $D_2=0.6$. The evaluation of D_1 and D_2 and L through the learning procedure is shown in Fig.6 and 7, respectively. In Fig. 8, the evaluation of δ_{art} and vigilance parameter ρ is given. For example, in Fig. 6 from 1st to 6th iteration, ART cannot perceive the "B" letter but in 7th iteration δ_{art} becomes less than 0.15 which is the reward level. In this case, ART is rewarded and "B" is stacked in the LTM.

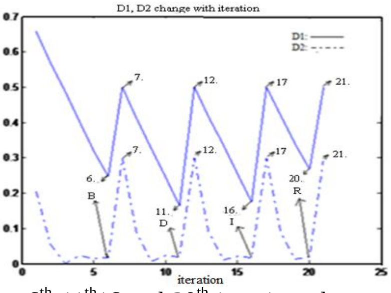


Fig. 6. For 6th 11th16 and 20th iterations, letters are about to be learned. After learning, at iterations 7, 12, 17 and 21 D1 and D2 are set to 0.5 and 0.3, respectively.

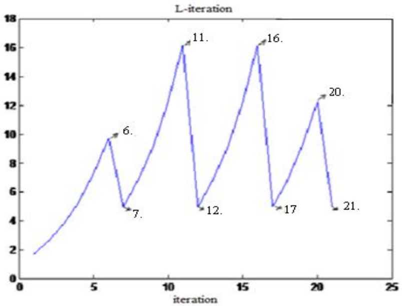


Fig. 7. At 6th, 11th, 16th and 20th iterations, letters are determined. For 7th, 12th, 17th and 21th iterations L is set to 5.

Here it must be noted that only the recognized letters are stacked at LTM as given in Fig. 9.

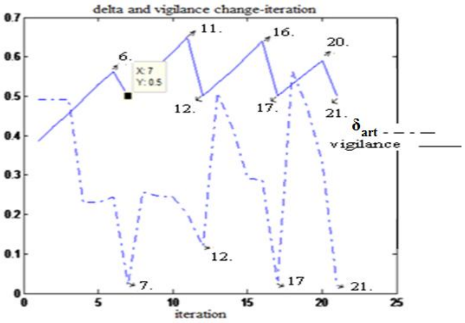


Fig. 8. For 6th,11th, 16th and 20th iterations, letters are determined. At 7th, 12th, 17th and 21th iterations, ρ is set to 0.5. Also, at these iterations, δ_{art} has the lowest values.

As it can be seen in the third block in Fig. 9, letter "I" and "B" are associated with letter "C" and "F" respectively, but as this association do not mix, “I” and “B”, they are accepted. Once all letters are stacked then RL organizes them to form the word.

Fig. 9 The patterns in LTM.

The ordering of these letters to form a word is accomplished by action selection system which adapts action selection according to RL. The initial values of the parameters W_r, W_C and W_V are small random numbers and the reward is 1 when a correct choice is done for a letter and it is assumed that the correct choice is set up if reward is obtained 20 times, successively. Each time the correct place of a letter in the word is determined, the next letter is considered. The change in values of W_r and $\delta_{as}(t)$ can be followed from Fig.10 and Fig.11, respectively. In 35 trials the average and mean number of the iterations is 428±86.13.

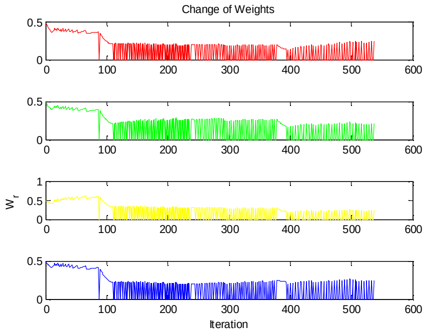


Fig. 10 Updating of wr during RL.

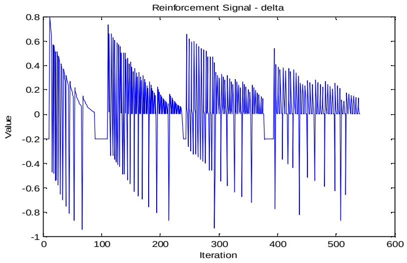


Fig. 11 Change of $\delta_{as}(t)$ during RL.

As it is depicted in Fig.11, for each of the four letters $\delta_{as}(t)$ fluctuates during the search for the correct place but once the correct place for the letter is found, $\delta_{as}(t)$ does not change anymore and also the value of W_r is stabilized. Once the place of a letter is determined correctly, search begins for the next letter and fluctuation in $\delta_{as}(t)$ begins again. When the action selection process is completed the letters are organized to form the word as shown in Fig. 12.

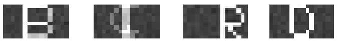


Fig. 12 The patterns ordered by action choices.

In order to see the effect of random initial valued weights, the problem is solved for 35 times. These results are shown in Table 1.

Table 1: ART’ s performance for 35 tests

For ART number of	B	I	R	D
Associated(clear) letters	23(12)	15(20)	19(16)	4(31)
Maximum iterations	9	10	8	7
Minimum iterations	3	2	4	3

4 CONCLUSIONS

In this work a novel structure combining ART and AS module is proposed. It is shown that ART-AS recognizes task related patterns and fulfils goal-directed behaviour. To confirm this property of ART, the analysis of the ART structure is given in detail considering differential equations defining it. The performance is tested with word hunting task and the simulation results are discussed.

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