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Fuzzy ART with Group Learning

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***Abstract*— Adaptive Resonance Theory (ART) is an unsupervised neural network based on competitive learning which is capable of learning stable recognition categories in response to arbitrary input sequences. In this study, we propose an application step, called "Group Learning", for Fuzzy ART in order to obtain more effective categorization. This new algorithm is called Fuzzy ART with Group Learning (Fuzzy ART-GL). The important feature of the group learning is that creating a connection between similar categories. We investigate the behavior of Fuzzy ART-GL with application to the recognition problems.**

I. Introduction

Adaptive Resonance Theory (ART) is an unsupervised neural network based on competitive learning which is capable of learning stable recognition categories in response to arbitrary input sequences. Fuzzy ART is a variation of ART, allows both binary and continuous input pattern. Fuzzy ART has limits of category space size by the vigilance parameter. Thus, input vectors are classified in each appropriate category. However, Fuzzy ART often makes input data of the common categories classify several categories.

In this study, we propose an application step, called "Group Learning", for Fuzzy ART in order to obtain more effective categorization. This new algorithm is called Fuzzy ART with Group Learning (Fuzzy ART-GL). The important feature of the group learning is that creating a connection between similar categories. This idea takes some sort of reference to Competitive Hebbian Learning proposed by Martinetz and Schulten.[1][2] We investigate the behavior of Fuzzy ART-GL with application to recognition problems. We apply the Fuzzy ART-GL to 2-dimensional input data and confirm its efficiency.

II. Learning Algorithm of Fuzzy ART with Group Learning

The proposed Fuzzy ART has an additional step, "Group Learning". Each category j corresponds to a vector $\boldsymbol{w}_j = (w_{j1}, \cdots, w_{jm})$ of adaptive weight. A connection between the winning category J and the second-winning category J_2 is created at each step. Fuzzy ART-GL has connections C and the age of connections, denoted by age. The similarity of input $\boldsymbol{I}$ and the second-winning prototype $\boldsymbol{w}_{J_2}$ is measured;

$$\frac{|\,\boldsymbol{I} \wedge \boldsymbol{w}_{J_2}\,|}{|\,\boldsymbol{I}\,|} \geq \rho. \tag{1}$$

If Eq. (1) is satisfied, a connection between J and J_2 is created;

$$C = C \cup \{(J, J_2)\}. \tag{2}$$

The age of the connection between J and J_2 is set to zero ("refresh" the age);

$$age_{(J,J_2)} = 0. \tag{3}$$

The age of all categories which directly connect with J are increased;

$$age_{(J,j)} = age_{(J,j)} + 1, \qquad j \in N_J, \tag{4}$$

where N_J is the set of categories which directly connect with J. The connections are removed, if the age is larger than $AT(t)$;

$$(J, j) \notin C, \qquad age_{(J,j)} \geq AT(t), \tag{5}$$

$$AT(t) = AT_i (AT_f / AT_i)^{t/t_{max}}, \tag{6}$$

where t_{max} is the learning length, AT_i and AT_f is the initial valued and the final value of AT, respectively.

III. Learning Simulation

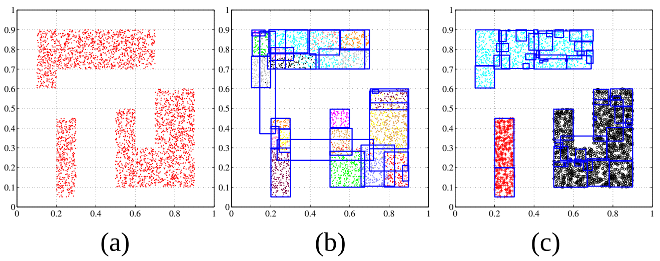

Fig. 1. Simulation result. (a) Input data. (b) Learning result of Fuzzy ART. (c) Learning result of Fuzzy ART-GL.

We consider 2-dimensional input data as Fig.1(a).

The learning results of Fuzzy ART and Fuzzy ART-GL are shown in Figs. 1(b) and (c). From these results, we can see that the proliferation of categories occurs with conventional Fuzzy ART. Furthermore, Fuzzy ART has a lot of categories in one cluster. In contrast, we can see that the proposed Fuzzy ART can recognize the group of the input data from its color as shown in Fig. 1(c). Therefore, the input data is effectively classified in each appropriate category.

References

[1] T. M. Martinetz and K. J. Schulten, "A 'Neural Gas' Network Learns Topologies," *Proc. of ICANN'91*, pp. 397-402, 1991.
[2] T. M. Martinetz and K. J. Schulten, "Topology representing networks," *Neural Networks*, vol. 7, no. 3, pp. 507-522, 1994.