17 - 7 Combining Overlapped Category Spaces Fuzzy ART

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1. Introduction

Adaptive Resonance Theory (ART) is an unsupervised neural network based on competitive learning which is capable of automatically finding categories and creating new ones. 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, to cover it, one category spaces overlap with different category spaces which include common inputs. In this study, we propose a new type of Fuzzy ART algorithm, Combining Overlapped Category Spaces Fuzzy ART. The important feature of the proposed Fuzzy ART is that different categories which include the same input data unite into one category.

2. Proposed Fuzzy ART

Fuzzy ART is composed of F_1 (input layer) and F_2 (category layer). The neuron i $(i = 1, \cdots, M)$ of F_1 and the neuron j $(j = 1, \cdots, N)$ of F_2 are connected by the bottom-up and the top-down weight vectors mutually.

Input vector: The M-dimensional input vector are denoted by $\boldsymbol{I} = (I_1, \cdots, I_M)$, where $I_i \in [0,1]^M$.

Weight vector: The top-down weight vector $\boldsymbol{w}_j = (w_{ji}, \cdots w_{jM})$ is the memory which belong to neuron j.

Parameters: Fuzzy ART dynamics are determined by a *choice parameter* $\alpha > 0$; a *learning parameter* $\beta \in [0,1]$; and a *vigilance parameter* $\rho \in [0,1]$.

Category choice: F_2 layer receives normalized input. The next step is to pass the information in F_1 up F_2, with the *choice function* T_j defined by;

$$T_j(\boldsymbol{I}) = \frac{|\ \boldsymbol{I} \wedge \boldsymbol{w}_j\ |}{(\alpha + |\ \boldsymbol{w}_j\ |)}, \tag{1}$$

where $(\boldsymbol{p} \wedge \boldsymbol{q})_i \equiv \min(p_i, q_i)$, $|\ \boldsymbol{P}\ | \equiv \sum_{i=1}^{M} |\ p_i\ |$, for any M-dimensional vector $\boldsymbol{p}$ and $\boldsymbol{q}$. For national simplicity, $T_j(\boldsymbol{I})$ is written as T_j.

The winning category, denoted by J, is found;

$$T_J = \max\{T_j : j = 1 \cdots N.\}. \tag{2}$$

Resonance or reset: *Resonance* occurs if the match function of the chosen category meets the vigilance criterion; that is, if

$$\frac{|\ \boldsymbol{I} \wedge \boldsymbol{w}_J\ |}{|\ \boldsymbol{I}\ |} \geq \rho, \tag{3}$$

Mismatch reset occurs if

$$\frac{|\ \boldsymbol{I} \wedge \boldsymbol{w}_J\ |}{|\ \boldsymbol{I}\ |} < \rho. \tag{4}$$

This continues until the chosen J satisfies (3).

Learning: Once (3) is fulfilled, the weight vector $\boldsymbol{w}_J$ is updated according to;

$$\boldsymbol{w}_J^{(new)} = \beta(\boldsymbol{I} \wedge \boldsymbol{w}_J^{(old)}) + (1-\beta)\boldsymbol{w}_J^{(old)}. \tag{5}$$

If all available F_2 nodes reset, new categories are established in F_2.

$$\boldsymbol{w}_{N+1} = \boldsymbol{I}. \tag{6}$$

In addition, to prevent (7) from monotone decreasing, let input $\boldsymbol{I}$ preprocess into the complement coding form.

$$\boldsymbol{I} = (\boldsymbol{a}\ ,\ \boldsymbol{a}^c) = (a_1, \cdots, a_M,\ a_1^c, \cdots, a_M^c), \tag{7}$$

where, $a_i^c \equiv 1 - a_i$.

Combining: If the category J overlap with other category k, inputs belonging to the category k is defined as belonging to the category J. The category k is erased, and the weight vector $\boldsymbol{w}_J$ is updated by;

$$\boldsymbol{w}_J^{(new)} = (I_{1min}, \cdots, I_{Mmin}, I_{1max}^c, \cdots, I_{Mmax}^c), \tag{8}$$

where I_{imin} and I_{imax} are the minimum and maximum value of input data I_i belonging to J, $I_{imax}^c \equiv 1 - I_{imax}$.

3. Simulation Results

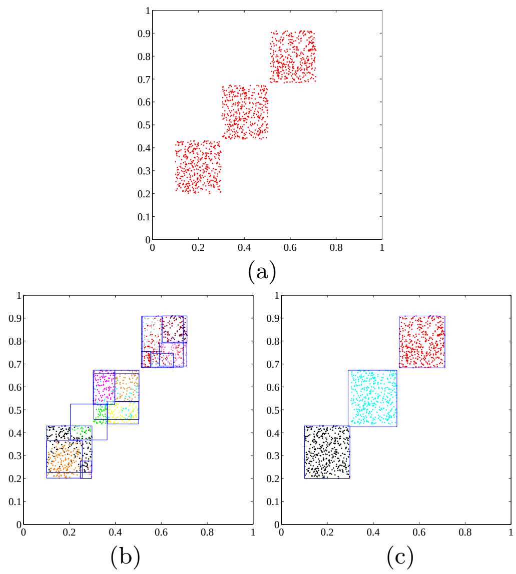

Figure 1: Simulation result. (a) Input data. (b) Simulation result of Fuzzy ART. (c) Simulation result of the proposed Fuzzy ART.

We consider the 2-dimensional input data as Fig.1 (a). The parameter for the learning are chosen as follows; $\alpha = 0.2, \beta = 1, \rho = 0.8$. The simulation results of the Fuzzy ART and the proposed Fuzzy ART are shown in Fig.1 (b) and (c). We can see that Fuzzy ART has a lot of categories at one cluster. However, from the result of the proposed Fuzzy ART, we can see that different categories, which include the same input data, unite into one category. Consequently, we can see clear categories. Hence, the proposed Fuzzy ART is effective.

4. Conclusions

In this study, we have proposed Fuzzy ART. By using this method, we can solve problems in Fuzzy ART. In the future, we try to adapt control engineering area and improve this study.