Performance enhancement for fuzzy adaptive resonance theory (ART) neural networks

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A modified fuzzy adaptive resonance theory neural network (ART) is used as a classifier for a texture recognition system. The system consists of a wavelet based low level feature detector and a high level ART classifier. The performance improvement is measured in terms of identification accuracy and computational burden.

Introduction: The adaptive resonance theory neural network (ART) as suggested by Grossberg [1] is a useful tool for pattern recognition. The original ART architecture (ART1), however, is capable of processing binary inputs only. The fuzzy ART [2] overcomes some of the limitations of ART1. While it has a similar architecture to that of ART1, it can process continuous valued data, and has a fast and stable learning procedure. The proposed feature-adaptive fuzzy ART self-organises not only the network weights but also the number of features at the input layer.

Feature-adaptive fuzzy ART: The fuzzy ART like all other ARTs constitutes an unsupervised learning scheme which can only self-organise its bottom-up, top-down and output nodes during classification. In complex texture classification applications, however, predetermined fixed construction of the input nodes or 'features', is not effective since different patterns could have the same features at certain feature detection levels. Flexible adaptation of feature detectors at the input level is essential as more complex textures are added to the classification pool.

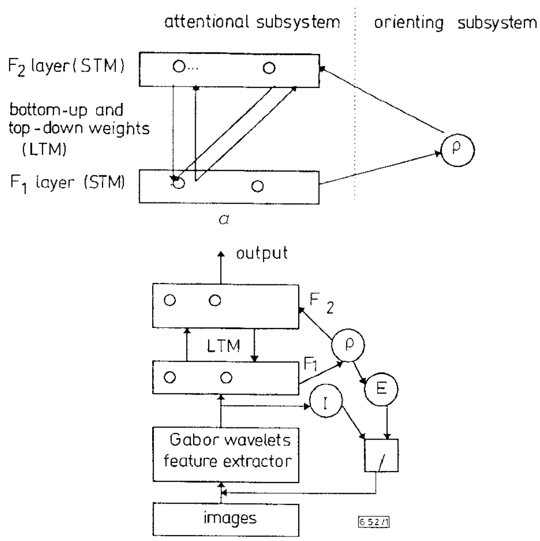

Fig. 1 *Structure of fuzzy ART1 system and adaptive feature fuzzy ART system*

a Fuzzy ART system
b Adaptive-feature fuzzy ART system

The proposed feature-adaptive fuzzy ART has all the features of the fuzzy ART such as adaptive search procedures, ability to operate in non-stationary conditions, self-organisation of its bottom-up and top-down nodes, and ability to cope with analogue data. It however, possesses unique characteristics that enable it to simulate the capacity of the high level cells used in the attentive processes of the visual system in a manner similar to the post-natal development of the human visual system where the feature detection ability is enhanced and refined over a period of time through complex visual stimulus.

The proposed input level self-organising process starts by learning through a simple input vector and continuously augments and refines the input layer by using more feature detector receptors as the test environment expands. This is to ensure a self-organising evolutionary model of artificial vision bearing some similarity to the post-natal development of the human visual system. This stepwise expansion of the feature vector will also reduce the computational burden in real-time applications. Two counters which keep track of the number of inputs and errors of the system, 'I' and 'E', respectively, in Fig. 1*b*, are added to the fuzzy ART system. After a certain number of tests, the system checks the number of failures, and an error ratio, Er, is computed as $Er = E/I$. The error ratio is compared to a pre-set threshold that satisfies the requirement of the system user. If Er is smaller than some threshold (92% in this work), the system resets both counters and prepares for the new input, otherwise, the system expands its inputs by adding more feature detector receptors (wavelet filters). This ensures the self-regulation of the system whenever the classification performance is below an acceptable level. Fig. 1 compares the conventional fuzzy ART with the proposed scheme.

Table 1: Comparison of classification accuracy of feature-adaptive and fixed-feature systems

Number of textures	Adaptive feature, feature size	Fixed feature, feature size	Fixed feature, feature size	Fixed feature, feature size
10	0.92 (4)	0.92 (4)	0.95 (8)	0.96 (12)
20	0.91 (4)	0.91 (4)	0.93 (8)	0.94 (12)
30	0.92 (4)	0.83 (4)	0.92 (8)	0.93 (12)
40	0.90 (8)	0.71 (4)	0.90 (8)	0.92 (12)
50	0.92 (12)	0.65 (4)	0.83 (8)	0.92 (12)

Experimental results: A two tier texture identification architecture, low level feature extraction and high level ART cognition, is used to test the proposition. The low level feature extraction is based on wavelet receptors tuned to certain frequencies and orientations [3]. The high level cognition is based on a fuzzy ART. 50 textures from the Brodatz album are used in the experiments. During the control experiments, several fixed size feature vectors are generated through wavelet based receptors. These feature vectors are then used at the input layer of a fuzzy ART. In the proposed modified ART configuration the feature vector starts with only four components and as more textures are introduced, the feature vector is expanded by adding more receptors. The results are shown in Table 1.

Conclusion: The evolutionary approach for the input layer adaptation of fuzzy ARTs for pattern recognition enhances and optimises the performance by modifying the number of input receptors required at each level of the test environment. The addition of two counters to the conventional fuzzy ART synchronises and regulates this flexible input operation.

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