ASIAN JOURNAL OF CIVIL ENGINEERING (BUILDING AND HOUSING) VOL. 1, NO. 4, (2000)
PAGES 69-75

APPLICATION OF THE MODIFIED ART2 ARTIFICIAL NEURAL NETWORK IN CLASSIFICATION OF STRUCTURAL MEMBERS

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ABSTRACT

In this research the basic algorithm of ART2 neural network has been modified for proper and efficient classification of vectors. In the basic architecture of ART2, the length of vectors is neglected. This causes error in sorting; paralell vectors with different length are classified in the same category. To overcome this deficiency, a virtual input neuron is added to consider vector length. The modifiend architecture not only considers the similarity of vectors direction but also considers the magnitude of vectors in sorting. ART neural networks are classified as unsupervised learning nets, a method is presented for supervised learning of ART2 without general changes in the basic algoithm.

Keywords: artificial neural network, adaptive resonance theory, ART2, structural element classification, supervised learning

1. INTRODUCTION

An artificial neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the human neurons. The processing ability of a network is stored in the interunit connection strengths, or weighs, obtained by a process of adaptation to, or learning from, a set of training patterns [3]. There are many kinds of artificial neural networks that are different both in architecture and their ability. In this paper attention is paid to the use of ART (Adaptive Resonance Theory) networks and their ability in sorting of structural elements.

2. ART NEURAL NETWORKS

ART networks are configured to recognize invariant properties of a given problem domain: when presented with data pertinent to the domain, the network can categorize it on the basis of this features. This process also categories when distinctly different data are presented, including the ability to create new. ART networks accommodate these requirements through interactions between different subsystems, designed to process previously encountered and unfamiliar events, respectively [12]. Two kinds of ART networks have been studied and can be

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distinguished essentially on the basis of the form of input information. They can accept binary or continuous inputs and on the approach used to process only this information. An ART network can process only binary input data and ART2 networks designed to process continuous input pattern data. A special characteristic of such networks is the plasticity that allows the system to learn new concepts and at the same time retain the stability that prevents destruction of previously learned information. ART networks accommodate these requirements through interactions between different subsystems, designed to previously encountered and unfamiliar events [2].

3. ART2 NETWORK

Adaptive Resonance Theory (ART) networks which were developed by Grossberg and Carpenter are self-organizing neural networks, and can be classified in unsupervised learning nets. ART nets automatically detect clustering and form classes of the data structure. A typical architecture of ART2 is illustrated in Figure 1. In this figure s_i is the i^{th} component of input vectors. W_i, x_i, u_i, v_i, p_i, q_i and y_i are called short term memories (STM). b_{ij} and t_{ji} are long term memories (LTM) of ART2 net [1].

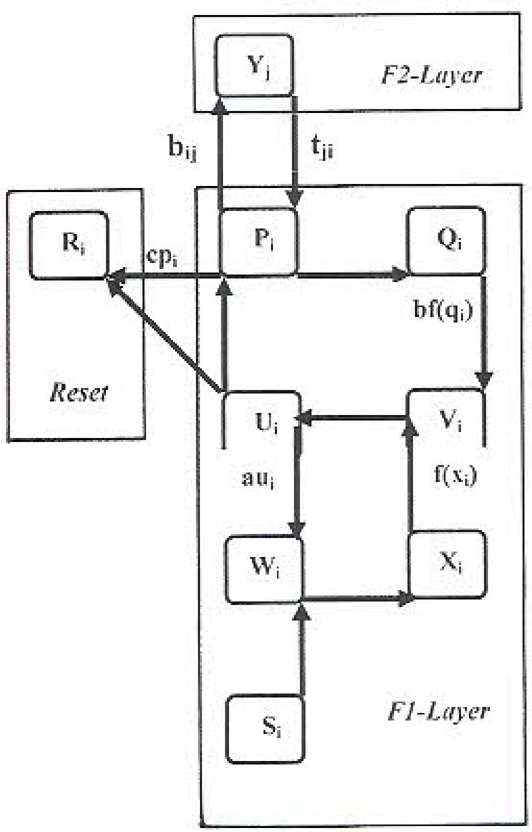

Figure 1. Typical ART2 architecture

The update F1 activations are:

$$u_i = \frac{v_i}{e + \|V\|} \tag{1}$$

$$w_i = s_i + au_i \tag{2}$$

$$p_i = u_i + dt_{ji} \tag{3}$$

$$q_i = \frac{p_i}{e + \|P\|} \tag{4}$$

$$v_i = f(x_i) + bf(q_i) \tag{5}$$

So that e, a small parameter introduced to prevent division by zero, $\|V\|$, vector Length, a and b fixed weights in the F1-layer, d, activation of winning F2 unit, θ, noise suppression parameter and α is the learning rate.
The activation function is:

$$f(x) = \begin{cases} x & \text{if} \quad x \geq \theta \\ x & \text{if} \quad x \langle \theta \end{cases} \tag{6}$$

Input signals to F2-Layer are:

$$y_i = \sum_i b_{ij} p_i \tag{7}$$

and weight updates for winning unit J are:

$$t_{ji} = \alpha du_i + \{1 + \alpha d(d-1)\} t_{ji} \tag{8}$$

$$b_{ij} = \alpha du_i + \{1 + \alpha d(d-1)\} b_{ij} \tag{9}$$

4. MODIFIED ART2 NEURAL NETWORK

An ART2 network categorizes vectors by the similarity between them. In the basic architecture of ART2 network that introduced by G. Carpenter and S. Grossberg [6] the similarity is based on the direction of the vectors. If the angle between two vectors is zero, the similarity of this two vectors is 100% and in this condition ART2 network places this two vectors in one category by a vigilance parameter equal to one. In the basic architecture of ART2 the length of the vectors is neglected. This causes error in sorting of vectors when the magnitude of sorted vectors is important for user. For example, two parallel vectors that have a very different length can be placed in a similar category, but two vectors having a little difference in length and direction could be placed in two different categories. The following example will clarify the discussion: In matrix A each column represent a three-components vector.

$$[A]=\begin{bmatrix} 1 & 2 & 1 & 2 & 1 & 5 & 4 & 5 \\ 3 & 6 & 3 & 6 & 3 & 3 & 3 & 3 \\ 5 & 10 & 5.2 & 10.4 & 6 & 7 & 7 & 7.5 \end{bmatrix}$$

Here three categories are defined for sorting of eight vectors in Matrix A. The result of sorting based on the basic ART2 net is shown in Table 1.

Table 1 Sorting of vectors based on the basic ART2 algorithm

No. of categories	Category	Category 2	Category 3
Classified Vectors	1,2,3,4,5	6,8	7

Vector 1 is parallel with vector 2, and vectors 3 are parallel with vector 4. Vectors 1, 3, and 5 are almost the same, but vectors 2 and 4 are completely different from the previous vectors. As it observed, the basic ART2 architecture places the first five vectors in one category. In the modified version of ART2 net, by adding a virtual input neuron to the net structure the above deficiency is removed, but also it considers the magnitude of vectors in sorting. In the modified version, for a vector containing n components, n+1 neurons for the input layer are defined. The last inpt component is an additional component that is called a *Virtual Neuron*, and its magnitude is equal to the square length of the vector, and can be determined as follow:

$$S_{n+1} = \sum_{i=1}^{n} S_i^2 \tag{10}$$

By using this additional component for the input vectors, ART2 network considers the magnitude of the vectors in addition to their direction, and a vigilance parameter is applied simultaneously for both magnitude and direction of input vectors. By this modification the ART2 network categorize vectors correctly, as for the previous example the results of the sorting based on the modified ART2 is shown in Table 2.

Table 2. Sorting of vectors based on the modified ART2 algorithm

No. of categories	Category 1	Category 2	Category 3
Classified Vectors	1,3,5,	2,4	6,7,8

5. APPLICATION OF ART2 NEURAL NET IN SUPERVISED LEARNING

Basically ART2 neural net is categorized in the group of unsupervised neural nets. In this discussion a method is presented in which ART2 operates as a supervised net without total changes in the basic algorithm.

In this approach the net training is accomplished in the following two stages:
The first stage that is called the *training mode*, ART2 net is trained by the input training vectors. Each input vector has an additional component, which carries a significant number; vectors that are categorized in the same group have an equal number in the last component. Actually this last component is the modification which has been made on the basic ART2 network. At the beginning of the training process all vectors are applied to the net by vigilance parameter equal to one. With this vigilance parameter each vector is categorized in its own category and vectors with equal components will be in the same category. Then ART2 net calculates top-down and bottom-up weights for every category disregarding the last additional component of vectors, which described earlier.

The second stage of the proposed method that is called the *test mode*, a vector is applied to the net with a desirable vigilance parameter. ART2 net calculates top-down and bottom-up weight for this vector without any modification in the last calculated weights. Then ART2 net compares this vector to the categories with this new vigilance parameter. If similarity between this vector to a category is greater than vigilance parameter this vector will be classified in this category. But the actual classification belonging to the vector, is the number of last additional component of the first vector in this category. In the test mode stage, the calculated top-down and bottom-up weight does not change, because the first calssification did not change in any level of the testing mode.

6. APPLICATION OF ART2 NET IN STRUCTURAL ENGINEERING

The modified ART2 neural net can be applied in sorting and categorization of structural elements. The approach can be used in sorting steel structural elements such as beam-columns, columns, beams and bracing system etc. without direct design of elements. As an example, the net is trained to categorize different non-standard latticed steel beam-columns made of the following elements:

2IPE140 latticed with PLs 160×8 mm @150 mm c/c
2IPE160 latticed with PLs 160×10 mm @150 mm c/c
2IPE180 latticed with PLs 220×8 mm @200 mm c/c
2IPE200 latticed with PLs 220×10 mm @200 mm c/c
2IPE270 latticed with PLs 300×10 mm @300 mm c/c

For this purpose a FORTRAN based program is used to prepare the training pairs. In this program the maximum axial force and bending moment considering different lengths for the proposed beam-columns are calculated. Each output training vector has four components: length of elements, axial force, bending moment and the type of column section.

The following limitations have been imposed on the training pairs: axial force is taken between 0 and 700 KN with 2 KN increment in each step, bending moment is taken between 0 and 200 KN.m with 2 KN.m increment in each step and the length of elements is taken between 2.5 m to 4 m with 0.1 meter increment in each step. By imposing the above limitations the outputs of the mentioned program was 8391 vectors. The net is trained based on the prepared training vectors, top-down and bottom-up weights are calculated in the training mode stage. In the test mode stage, the design results of an eighteen floors steel structure building were presented to the net and modified ART2 net classified all beam-columns in the correct categories with 0% error. To demonstrate the efficiency of the net, the mentioned steps in generating the training pairs are altered and the net results are summarized in Table 3.

Table 3. Effects of increments (Incr) on training pairs generation and their classification

Length of element (meter)			Axial force (KN)			Bending moment (KN.m)			Percentage of error in classification
Min	Max	Incr.	Min	Max	Incr.	Min	Max	Incr.	
2.5	4	0.1	0.0	700	2	0.0	200	2	0.0
2.5	4	0.2	0.0	700	2	0.0	200	2	0.44
2.5	4	0.1	0.0	700	5	0.0	200	2	0.26
2.5	4	0.2	0.0	700	5	0.0	200	2	0.71
2.5	4	0.1	0.0	700	2	0.0	200	5	0.61
2.5	4	0.2	0.0	700	2	0.0	200	5	0.79
2.5	4	0.1	0.0	700	5	0.0	200	5	0.79
2.5	4	0.2	0.0	700	5	0.0	200	5	0.97
2.5	4	0.5	0.0	700	10	0.0	200	10	23.83
2.5	4	0.5	0.0	700	10	0.0	200	20	26.41
2.5	4	0.5	0.0	700	20	0.0	200	10	25.41
2.5	4	0.5	0.0	700	20	0.0	200	20	33.28

7. CONCLUSIONS

In this paper ART2 artificial neural network has been modified for proper sorting of the input vectors. First a *Virtual Neuron* is introduced to the basic algorithm to consider length of vectors. This input *Virtual Neuron* improves the efficiency of the ART2 neural net, where the length of vectors is considered in sorting. Second, an *additional component* for each input vectors is introduced. This additional component is a number that carry a significant information about the categorization of vectors. This component helps the network in arrangement of vectors in the final categorization. By this second modification ART2 neural network operates as a supervised ART2 network is used as a structural steel or concrete element classifier for design purpose in a minimum time and effort especially for built-up members. This procedure can be summarized in the following two steps:

In the first step that is called the *training mode*, the net is trained based on the input vectors. In this mode network learns to categorize the vectors for the next application. Then in the second step that is called the *test mode*, network can categorize any input vector that is applied to the net with previous learning. Choosing small increments in the training mode will result in an exact classification of vectors.

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