Adaptive Pattern Classification Using Fuzzy ARTMAP

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ABSTRACT

We have investigated the fuzzy ARTMAP neural network architecture to solve pattern clasification problems. ARTMAP is a class of neural network architecture that perform incremental supervised learning of recognition categories and multidimensional maps in response to input vectors presented in arbitrary order. Fuzzy ARTMAP is a generalized ARTMAP to deal with analog or binary input vectors. This generalization accomplished by replacing the ART1 modules of the binary ARTMAP with fuzzy ART modules. Fuzzy ARTMAP is easy to use and differs from many previous fuzzy pattern recognition algorithms which perform off-line optimizationof a criterion function. The one we have used for the evaluation in this research is that of the two-dimensional binary XOR gate problem, generalized to real-valued two-dimensional vectors. The performance of the fuzzy ARTMAP is compared with Nearest Neighbor pattern classification, decision surface mapping methos(DSM), and a two-layer perceptron trained by error back propagation. The fuzzy ARTMAP outperforms these methods with respect to error rates and the number of prototypes required to describe class boundaries.

INTRODUCTION

Neural network applications for pattern classification or recognition have been developed by many researchers in industries and universities. Some of the conventional approaches including back propagation, Bidirectional Associative Memory(BAM) and Hybrid learning networks show good robustness for the performance criteria[1][2]. However, it cannot be denied that some problems exist such as learning rate limitations, difficult in selecting the optimal number of hidden units and limitations of memory capacity, which shows

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that they might be affected by the characteristics of input patterns. Evenmore, they tend to destroy previous learning whenever more training patterns are added to increase the performance of the network where a large number of input patterns are concerned.

Those problems can be tolerated by using ARTMAP architecture, a supervised learning system built up from a pair of Adaptive Resonance Theory modules(ARTa and ARTb) that are capable of self-organizing stable recognition categories in response to arbitrary sequences of the input patterns[3]. The one we have tested among ARTMAP architectures is a Fuzzy ARTMAP which is consist of two Fuzzy ART modules [4]-[6]. The performance of the fuzzy ARTMAP is compared with Nearest Neighbor pattern classfication, Decision Surface Mapping method(DSM), and a two-layer perception trained by the error backpropagation [7]. The simulation results with the two-dimensional generalized XOR gate show that the fuzzy ARTMAP neural network architecture provides a simple means of robust classification of adaptive pattern classfication problems.

FUZZY ARTMAP ARCHITECTURE

The fuzzy ARTMAP incorporates two fuzzy ART modules, ART_a and ART_b , that are linked together via an inter-ART module, F^{ab}, aclled a map field. The map field is used to form predictive associations between categories and to realize the match tracking rule, whereby the vigilance parameter of ART_a, ρ_a, increases in response to a predictive error is not repeated on subsequent presentations of the input. The BASIC architecture of of fuzzy ARTMAP is shown in Fig. 1. During the training period, the ART_a modulereceives a data stream {a} of input patterns and ART_b receives a data stream {b} of target patterns, where b is a corresponding target to a. If a vector a is associated with a vector b, then any other input that activates the a's category node will predict the category of target pattern b.

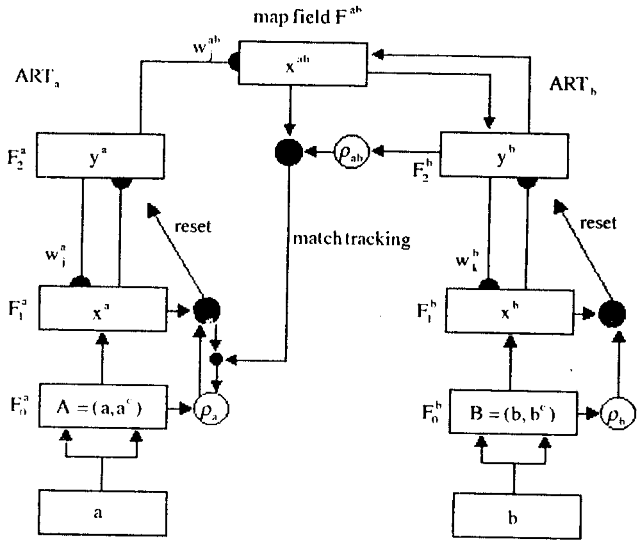

Figure 1. Fuzzy ARTMAP architecture

However, when a mismatch at the map field between the ART_a category activated by an input a and the ART_b category activated by the input b occurs, the net increasesthe ART_a vigilance parameter, ρ_a, by the minimum amount needed to search for and, if necessary, create a new cluster(category). The new cluster is created to learn a new ART_a category whose prediction matches the ART_b category. After the training is completed, which means the net predicts a correct corresponding target pattern for each of the training input patterns, the test input patterns are presented at ART_a without the use of ART_b.

Because of the combinations of match tracking and fast learning, the fuzzy ARTMAP neural network can learn a different prediction for a rare event than for a cloud of similar frequent events in which it is embedded. In other words, the fuzzy ARTMAP establishes different categories for very similar ART_a inputs that make different predictions, while also allowing very different ART_a inputs to form categories that make the same prediction. To improve the classification results, we used the voting strategy approach in fuzzy ARTMAP, in fast learning, typically leads to different adaptive weights and recognition categories for different orderings of a given training set, even when the overall predictive accuracy of all simulations is similar. The different category structures cause the set of test set items, where error occur, to vary from one simulation to the next. The voting strategy used for fuzzy ARTMAP requires the training set to be presented to the network serveral times with different orderings. Before each individual simulation the input ordering is randomly assembled. The prediction of each test set item is recorded after each simulation. Voting selects the outcome predicted by the large number of simulations. The number of votes cast for a given outcome provides a measure of predictive confidence at each test set point. Since the set of items making erroneous predictions varies from one simulation to the next, voting cancels many of these errors. Therefore, this voting strategy can be used to assign confidence estimates to competing predictions given small, noisy, or incomplete training set. More details about fuzzy ARTMAP and learning algorithms of fuzzy ART can be found in [4],[5] and[6].

PERFORMANCE ASSESSMENT AND EXPERIMENTAL RESULTS

The generalized(real-valued) two-dimensional XOR gate(Figure 2), as one of the simple examples, was used to demonstrate the performance of fuzzy ARTMAP, compared with those of some other networks[7].

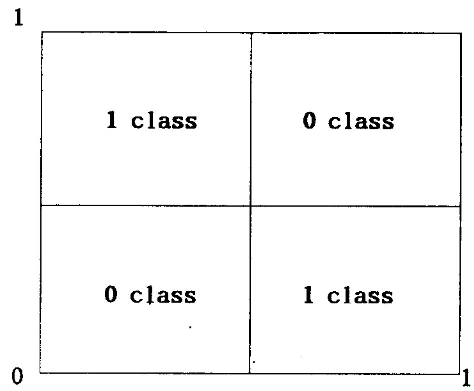

Figure 2. A generalized two dimensional XOR gate

All training inputs were taken at random and a test set of 6400 samples was at random. The performance of fuzzy ARTMAP was checked at every increment of 1000 training samples until the net reached a sufficiently small error rate. Ten independent experiments with both conservative mode and forced choice mode were executed and the results of the experiments were averaged. And five voting strategy in fuzzy ARTMAP was tested with 200 and 6400 training samples. Table 1 and Figure 3 illustrate the averaged results of the net with the generalized XOR gate.

Table 1.
Average error rates with V_a=0.9(conservative mode) & V_a=0.71(forced choice mode)

No. of Training Sample	error rates(%) V_a=0.9	error rates(%) V_a=0.71
200	15.04	5.29
1000	2.32	1.67
2000	1.03	1.07
3000	0.77	0.94
4000	0.68	0.77
5000	0.62	0.68
6400	0.48	0.56

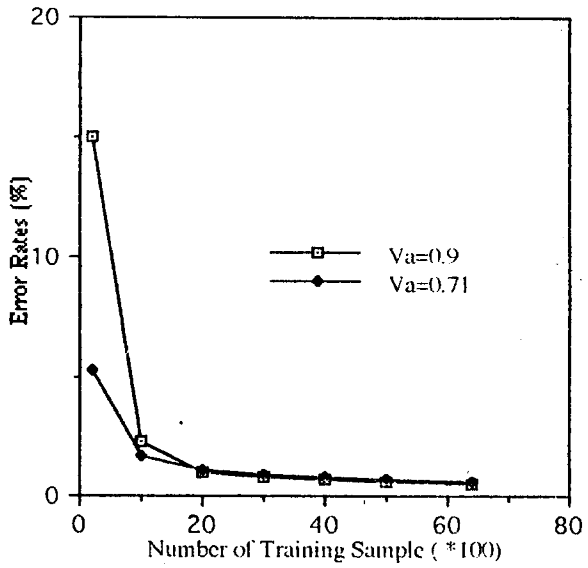

Figure 3. Average Error Rates with V_a=0.9 and V_a=0.71

The average error rate of fuzzy ARTMAP trained with 6400 samples drops to 0.56 % in the forced choice mode (V_a=0.71) and 0.48% in the conservative mode (V_a=0.9), where LVQ1 produces the range of error rates between 1.2% and 6%, Back Propagation between 0.42% and 0.7%, DSM between 0.08% and 0.35%, and NN keeps the error rates of 0.84% in Shlomo's paper [7]. In our comparison, DSM has the best average error rate of 0.08 % , but it is highly affected by the number of prototypes with which DSM is trained. And the error rates of BP and LVQ1 are also dependent on the number of prototypes. However, in the case of fuzzy ARTMAP it does not need to assign how many prototypes(or clusters) should be used to get the best performance, because it is increases clusters automatically if it needs to. And also, it is easy to train by using a trial-by-trial method which means to add a certain amount of training samples until a sufficiently small error rate is achieved. When we applied five voting strategy with 200 and 6400 training samples at V_a=0.9, the averaged error rate drops to 9.97 % from 15.04 %, 0.16 % from 0.48 %, respectively. Using the voting strategy for fuzzy ARTMAP does not have much influence with 6400 training samples, whereas the error rate is considerably improved with 200 training samples. Therefore, we can increase the classification rates with the voting strategy when the availability of training input patterns is not plentiful. Another characteristic of the net is that a high vigilance(conservative mode) can be used under the certain environment where errors carry a high price. For example, the error rates with conservative mode and forced-choice mode are close enough with 6400 training samples for above experiments, but the rate of no-responses which are counted as error is 67.6 % among the errors with 200 training samples at V_a=0.9, whereas it is 7.71 % at V_a=0.71. That means the fuzzy ARTMAP produces no-response errors rather than misclassified errors with a high vigilance parameter where the training samples are not enough.

CONCLUSIONS

We tested the fuzzy ARTMAP to show a good robustness in the generalized XOR gate problem. It is a very efficient neural network where a large amount of input data set should be considered in training a network. Our results demonstrate that the conventional problems in neural network approach to pattern classification tasks such as learning rate limitations for stability of the net, initial weights setting problems to avoid local minima, difficulty in selecting the optimal number of hidden units to get best performance, can be solved by using the fuzzy ARTMAP. Evenmore, it keeps more previous learning patterns whenever more training patterns are added to increase the performance of the network where a large number of input patterns are concerned. Unlike other neural networks, only new input samples will be trained without re-training old input samples. We will investigate more practical applications with fuzzy ARTMAP, such as automated cardiac arrhythmias classification problem [8]-[9], jamming signal detection in radar signal processing, or development of more reliable hand-written character recognition system.

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