Improving Pattern Recognition using Several Feature Vectors

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Abstract. Most pattern recognition systems use only one feature vector to describe the objects to be recognized. In this paper we suggest to use more than one feature vector to improve the classification results. The use of several feature vectors require a special neural network, a supervised ART2 NN is used [1]. The performance of a supervised or unsupervised ART2 NN depends on the appropriate selection of the vigilance threshold. If the value is near to zero, a lot of clusters will be generated, but if it is greater, then must clusters will be generated. A methodology to select this threshold was first proposed in [2]. The advantages to use several feature vectors instead of only one are shown on this work. We show some results in the case of character recognition using one and two feature vectors. We also compare the performance of our proposal with the multilayer perceptron.

Keywords: Pattern Recognition, Supervised ART2 Neural Network, Multilayer perceptron, Digit recognition.

1 Introduction

In general, pattern classification involves mapping a pattern correctly from the so-called feature space into a class-membership space [4]. The decision-making process in pattern classification can be thus summarized as follows. Consider a pattern represented as an n-dimensional feature vector.

$$X = [x_1, x_2, ..., x_n] \tag{1}$$

The task is to assign this vector to one of the K classes $C_1, C_2, ..., C_K$. Any supervised or unsupervised approach needs the description of the objects as a feature vector.

In this paper we propose how to use de ART2 NN in a supervised way, using several feature vectors, instead of only one. Results for digit recognition are also presented.

2 State of the Art

In [], the authors…

3 Methodology used

In this section the supervised version of the ART2 NN is briefly described. For the correct functioning of this supervised version, the following points are considered.

3.1 Sub-feature vectors

A supervised version of the ART2 is used in this paper. The advantage when using a supervised neural network is that we always know which features describe which object.

3.2 Threshold selection

The functioning of the ART2 NN is based on the selection of the vigilance threshold ρ. If a small value is selected, then similar features will be put in different clusters and then a lot of clusters will be generated. In the other hand, if a greater value is selected, then many clusters will be generated. This means that different features will be merged into the same cluster.

3.3 Training

For each SFV a classifier with its corresponding MM and ART2-NN as the one shown on Fig. 1 are used. The MM is a bi-dimensional array connected to the output of the ART2-NN with as many rows as clusters generated by the ART2, and as many columns as objects to recognize. The number of clusters generated by the ART2 depends on the vigilance threshold ρ [3]; it is during the training of each ART2, that each MM is constructed. The value on each cell of a particular MM represents the times a SFV is present on each object.

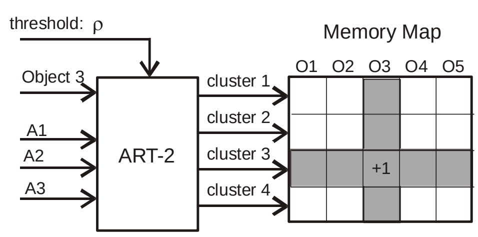


Fig. 1. Supervised ART2-NN during training.

3.4 Indexing

During this stage the set of SVFs extracted from a test image are used to retrieve from the MM the objects that produced that SFVs giving as a result a list of candidate models. This list is finally reduced by means of a threshold mechanism. These two indexing steps are next explained in more detail.

3.4.1 Candidate selection

During this step, each SFV in the test image is presented to the supervised ART2-NN. If this SFV is closed enough to one of the SFVs already learned by the NN then the corresponding NN's output would be turned on, selecting a row of the MM. Those objects for which their corresponding location values in this row are greater than 0 will receive the votes into the evidence-register. This process is repeated for each SFV in the test image. At the end of this process we will have as a result the set of hypotheses arranged as a histogram of votes. This histogram is obtained from the evidence-register.

3.4.2 Candidate reduction

At the end of the candidate selection process we will have a histogram containing the number of votes that each model has received during this process. Intuitively, those objects with more votes are the best candidates. One way to decide which objects are present in the input image is by using a selection-threshold σ. This value is obtained considering the number of SFVs describing each object.

4 Experimental Results

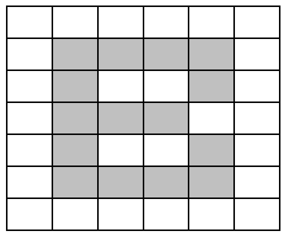
In this section the performance of the supervised ART2 NN and the multilayer perceptron is tested in the case of the digit recognition. Three different scenarios are considered:

1. Digit recognition with the supervised ART2 NN, using two SFVs.
2. Digit recognition with the supervised ART2-NN using one SFV.
3. Digit recognition with the multilayer perceptron using backpropagation.

Each digit is described by two SFVs. The first SFV incorporates the number of black cells for each row; the second one comprises the number of black cells for each column is computed. An example is shown on Fig. 2.

For each object on Fig. 3, the SFVs are obtained, and the procedure to select the vigilance threshold for each SFV described in Section 2.2 is applied.

For a given set of digits, these two features vectors are computed. In scenario 1, these two SFVs are used, each one with its corresponding supervised ART2-NN. In scenarios 2 and 3 we consider these two SFVs, but these are represented using just one SFV, for the example on Fig. 2, the SFV is given by [0,4,2,3,2,4,0,5,3,3,4,0]. For each digit, 4 different patterns were used during training, a total of 40 different patterns were used during training. Fig. 3 shows the training set.



SFV_1=[0,4,2,3,2,4,0]

SFV_2= [0,5,3,3,4,0]

Fig. 2. Extraction for the SFV1 and SFV2.

Tables 1, 2 and 3 show the results obtained. The initial value for the threshold was selected according to column *thr*. This column has the threshold value that a specific class needs to classify all the objects (maximize CD). Then the average of these values is the initial threshold value. For each threshold value, and for each class (each digit), the CC and CD values are calculated. Finally the difference between CD and CC are shown on the last row. The smallest value is selected as the vigilance threshold. Table 1 shows the results for scenario 1, for SFV1 (1.72). The results for the SFV2 are shown on Tables 2 and 3.

As we can see on Table 2 the selected threshold value is 2, nevertheless to guarantee a good selection, the procedure is repeated. The results on Table 3 show that the recommended value for the SFV 2 should be chosen between 1.4 and 1.2. We choose 1.3 as the threshold value. For scenario 2, the suggested threshold is 1.7 (see Table 4).

Threshold				1,72		2,06		2,24		2,41		2,58	
	Thr	CD	CC	CD	CC	CD	CC	CD	CC	CD	CC	CD	CC
ZERO	1,41	4	1	3	0	3	4	3	6	3	12	3	12
ONE	2,25	4	0	0	0	3	0	4	0	4	0	4	1
TWO	2,26	4	9	3	5	3	5	4	10	4	10	4	13
THREE	1,74	4	10	3	7	4	12	4	14	4	14	4	16
FOUR	1,42	4	36	4	0	4	3	4	4	4	4	4	4
FIVE	1,74	4	9	4	5	4	12	4	12	4	12	4	13
SIX	1,1	4	0	4	3	4	7	4	13	4	13	4	16
SEVEN	2,1	4	4	3	0	4	4	4	7	4	7	4	10
EIGHT	2,1	4	7	1	3	4	7	4	9	4	9	4	14
NINE	1,1	4	0	4	1	4	5	4	7	4	7	4	8
TOTAL	1,72	36	75	26	24	34	55	36	76	36	76	39	107
V		-39		**2**		-21		-40		-40		-68	

Table 1. Selected threshold values (scenario 1) for the first SFV.

The number on each cell of the memory map tells us how many times a feature was selected for an object. The rows are the number of clusters generated by the ART2 NN and the columns are the objects that we want to recognize. As we mentioned, the number of clusters generated by the ART2 NN depends on the threshold value, for the SFV1 a value of 1.72 was used, and 1.3 for SFV2.

On the memory map the features of each object are stored, during the training stage. The MM let us get information about the features shared by some objects.

Once the information has been trained and stored, a new object can be classified. The supervised ART2 NN selects the cluster that most resemble an input, that cluster is then selected. All the objects sharing that feature receive the number of votes previously stored during the training stage. At the final stage a list of candidates is obtained during the classification process. One of the advantages to select a set of SFVs, instead of only one, is that each SFV selects the objects sharing that feature.

Once the NN was trained for the 3 scenarios, different objects from those used during training are used. Some classification results are shown on Table 5.

The same patterns used to train the supervised ART NN were used to train a multilayer perceptron using the backpropagation rule. The 3 different NNs were tested with different objects used during training. A set of these objects is shown on Fig. 4. The classification results are shown on Table 5. As we can see from this table, the supervised ART2 NN (in the cases of one and two features vectors) shows a better performance than the multilayer perceptron. As we can see from Fig. 4, for objects b and d, the output given by the multilayer perceptron was digit 1, with the supervised ART2 NN; the given output was a most suitable digit than digit 1. In general the performance of the supervised ART2-NN was better than the multilayer perceptron.

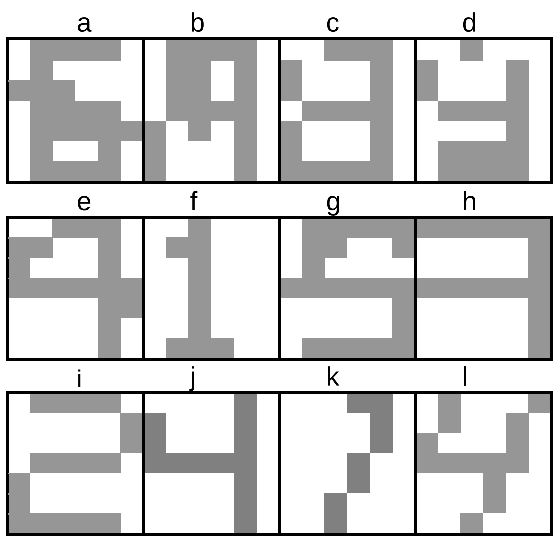


Fig. 4. Test set used for the 3 recognition cases.

As we have mentioned, the supervised ART2-NN gives a list of candidates indicating the objects that most resembling the object at the input. Table 5 shows the results for the test patterns on Fig. 4. The number of votes for each digit, and the number that is recognized, is indicated on it. For example, for object (a) on Fig. 4, the output of the supervised ART2-NN using two SFVs was 4 votes for digit 6, and 2 votes for digit 8; and using one SFV, it was 2 votes for digit 6 and 2 votes for digit 8. As we can see, the advantage of using two SFVs is that the object most resembling the input pattern, gets more votes than the others.

5 Conclusions and Directions for Future Research

In this paper we proposed to use a supervised ART2 NN using several feature vectors to recognize objects. The advantage to use several SFVs is that the information is distributed obtaining thus a better performance. Instead of having a candidate at the output, we get a list of ordered candidates in terms of the times they were indexed by each SFVs. This decreases misclassification. Another advantage is the using of a memory map. Here the information is stored and weighted. The information stored can be used to know where a given feature is found in an object. If it happens that different objects share a feature, the weight for this feature is proportional to the number of objects sharing it. On the other hand, if a feature belongs to just one object, then this feature is most relevant for that object.

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