IMPROVEMENT OF PATTERN RECOGNITION IN THE FIELD OF MAPPING USING NEURAL NETWORKS

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ABSTRACT

In this paper, we describe an improvement of pattern recognition in the field of mapping using neural networks. In fact IRSIT has made an attempt of pattern recognition in the field of mapping using classical pattern recognition techniques. This latter uses statistical pattern recognition. Our improvement is based on Basit Hussain's neural network paradigm using Boolean functions. Dealing with character recognition. We have tested the improvement on many maps and it outperforms the statistical one.

KEYWORDS

Mapping, Neural Networks, Boolean function algorithm.

1. INTRODUCTION

Nowadays we're living in a world where everything is being digitized. But this emerging phenomenon is facing obstacles that are disappearing from year to year. In fact, if we want to consider all the books, magazines, maps and so on existing on this planet to be digitized a rapid computation will show us that we need a million of man-year. So it is a huge investment in terms of money and humans. Nevertheless we're not facing only this problem; there is the decay that affects the documents, which lets them almost unusable. Pattern recognition constitutes the promised wave for the automated stage of digitalization.

Before introducing the algorithm used, let's discover the means of mapping [8]. Mapping means all the techniques of drawing: geographical, topographical and geological maps. It is a science, a technique and an art. In fact it is a science because it includes mathematics, geometry it is nothing but a geographical measure. It is a technique because the artist should gain a certain technique for representing the maps that require the respect of many rules. It is also an art, in producing aesthetic maps in their colors, shapes.
The common point between all the maps is that they contain various information. These latter are of five types, three among them are relative to geographical shapes and the two other are relative to appendix shapes.

The three types of geographical shapes are point, line, polygon and their associated symbol [8, 9]. Let's take an example:

- a point for a region's name,
- a line for a river,
- a polygon for a city.

The two other relative to appendix shapes are the following: annotation and position. The first one is used to annotate a map by inserting symbols and text whereas the second one is used to indicate direction, longitude, and latitude in a geographical map.

The precedent work for pattern recognition [7] uses classical pattern recognition and more precisely statistical pattern recognition. It consists of five modules operating on the shape to be recognized. This method after many tests made by IRSIT's engineers, proved to be insufficient if the pattern to be recognized includes black noise.
So we've interested in a new emerging technique which proved itself in pattern recognition: neural networks.

2. NEURAL NETWORKS

Neural networks are non-parametric rule learning system with highly parallel and simple architecture [2, 12, 15, 16, 17]. There are several types of neural networks such as Hopfield Networks, Boltzman machines, bi-directional associative memories and the MultiLayer Perceptron (MLP). All of them have an appropriate training rule derived in most cases of the HEBB's rule.

In neural networks there are two learning approaches: the supervised and the unsupervised one. The first one the network deals with the user to achieve its goal. The second one the network deals with its own for the same task.

2.1. CLASSICAL METHODS VS. NEURAL NETWORKS

In order to justify the choice of neural networks, we've made a comparison between them and classical methods [7] of pattern recognition (Table. I).

Classical methods	*Neural networks*
Symbolic	Sub symbolic
Seek the solution in a large discrete space in order to get conclusions	Sub symbolic methods calculate conclusions
Still work is needed in order to improve the capabilities of symbolic methods for uncertainty and noise	Are more ready for uncertainty and noise
Use of shape base	Use of training set
Deterministic: a unique result	Non-deterministic: a set of possibilities
Pre-treatment is required	No pre-treatment is required
Comparison between the pattern to be recognized with the ones inside the base of shape	Non comparison between the pattern to be recognized and the ones inside the training set
No recognition in case of absence of the pattern in the shape base	Recognition in case of difference between the pattern and the ones inside the training set
Non incremental learning	Incremental learning
User can predict the result of recognition	User can't predict the result of recognition
Sequential	Parallel

Table. I: *Comparison between classical methods and neural networks.*

After this comparison we've managed to find the appropriate algorithm for pattern recognition in the field of mapping using neural networks. In fact this algorithm should have in its own tools of translation, rotation, noise inclusion, scale change.

When studying the most used neural networks paradigms we've found that only Neocognitron [3, 4, 6, 13, 14] and Boolean function algorithm [10, 11] are the most suitable neural networks paradigms for pattern recognition in the field of mapping.

2.2. NEOCOGNITRON VS. BOOLEAN FUNCTIONS ALGORITHM

In order to choose between the two neural network paradigms, we've made at this point a comparison between them (Table. II)

Neocognitron	*Boolean functions algorithm*
Particularities	
- Use of pattern recognition technique by part by remembering the different parts of the pattern	- Use of pattern recognition schema with hierarchical subdivision
- Presence of two learning approaches: the supervised and the unsupervised	- Presence of one leaning approach: the supervised
- Use of HEBB's learning rule	- Use of a new learning rule based on weight adjustment
Strengths	
- More realistic	- Easy
	- Acceptable pattern recognition rate for deformed pattern and including noise
	- Convergence in one loop
	- Requires less neurons and connections
Weakness	
- Complex	- Non realistic
- Insensitive to translated patterns after one limit	
- Convergence in many loops	
- Requires many neurons and connections	

Table. II: Comparison between the Neocognitron and Boolean functions algorithm

2.3. IMPROVEMENT OF THE BOOLEAN FUNCTION ALGORITHM

The Boolean function algorithm is based on Boolean functions. The number of linearly separable Boolean function is fewer and they cannot be directly implemented because they require a pre-treatment [1].

In the Boolean function algorithm [10, 11] the pattern to be recognized is 16 x 16 pixels. This one is subdivided in 16 sub-patterns each one is 4 x 4 pixels. These sub-patterns are numbered from A1 to D4 (A1, A2, A3, A4, B1, B2, B3, B4, C1, C2, C3, C4, D1, D2, D3, D4).

As stated in Basit Hussain's paper that in order to recognise patterns shifted by ±2 either in x or in y or in both we need a layer of 25 neurons, but no information is given about the learning and recognition phase. So we've managed to develop two approaches to be included in the Boolean function algorithm. The first developed approach requires too much processor time and memory. These limitations has lead us to develop a second approach much better than the first one.

2.3.1. FIRST APPROACH

The first approach used for recognizing shifted patterns by ±2 is the following:

The neural network is constituted of two layers. The first layer is constituted of shifting neurons form (-2, -2) to (2, 2) for each sub pattern (Ai, Bi, Ci, Di) i ∈ (1, …, 4) which gives 400 neurons in entry. The second layer is constituted of neurons that detects the shifting of the whole pattern by a shift of (-2, -2) to (2, 2) which gives 25 neurons in output (N1, N2, …, N25). The output result of these neurons gives 25 θi (final vector output) (Fig. 1) with Wi (weight vector) in the second layer are all equal to 1 whereas the Wi of the first layer remains as it stated in the Boolean function algorithm.

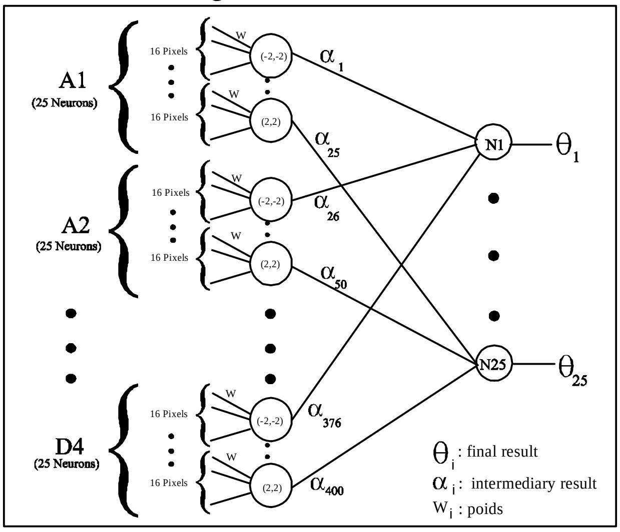

Fig. 1: First approach.

During the training phase for each pattern of the training set the θi with i ∈ (1, …, 25) are computed for all the neurons Ni with i ∈ (1, …, 25). But before we should determine each αi, i ∈ (1, …, 400) corresponding to the intermediary result, for each (Ai, Bi, Ci, Di), i ∈ (1, …, 4) 16 in all containing each 25 possible shifting from (-2, -2) to (2, 2).

The equations for neuron Ni are:

$$\theta_1 = (\alpha_1 + \alpha_{26} + \alpha_{51} + ...+ \alpha_{376}) \qquad (1)$$

and $$\alpha_1 = \sum_1^{16} Wa1_{(-2,-2)} * A1_{(-2,-2)} \qquad (2)$$

$$\alpha_{26} = \sum_1^{16} Wb1_{(-2,-2)} * B1_{(-2,-2)} \qquad (3)$$

.

and $$\alpha_{376} = \sum_1^{16} Wd4_{(-2,-2)} * D4_{(-2,-2)} \qquad (4)$$

During the recognising phase each pattern of the test set is compared to all the patterns of the training set. The comparison of one pattern of the training set to one pattern of the training set is as follows:

- compute the Pi (final vector output) with i ∈ (1, …, 25). The equations for Pi are:

$$P_1 = (\beta_1 + \beta_{26} + \beta_{51} + ...+ \beta_{376}) \qquad (5)$$

and $$\beta_1 = \sum_1^{16} Wa1''Ent''_{(-2,-2)} * A1''Test'' \qquad (6)$$

$$\beta_{26} = \sum_1^{16} Wb1''Ent''_{(-2,-2)} * B1''Test'' \qquad (7)$$

.

and $$\beta_{376} = \sum_1^{16} Wd4''Ent''_{(-2,-2)} * D4''Test'' \qquad (8)$$

- comparison of the Pi with θi and compute the number of occurrence K where Pi = θi,
- if K > 19 (fixed threshold) then the pattern is recognised else it isn't.

This approach requires 25 neurons having each 16 connections in the second layer for a given pattern and 25 comparisons between Pi and θi. This limitation is a shortage to the number of patterns to be recognized. The second approach reduces the number of neurons to 16.

2.3.2. SECOND APPROACH

The second approach used for recognizing shifted patterns by ±2 is the following:

The neural network is constituted of two layers. The first layer is constituted of shifting neurons form (-2, -2) to (2, 2) for each sub pattern (Ai, Bi, Ci, Di) i ∈ (1, …, 4) which gives 400 neurons in entry. The second layer is constituted of 16 neurons, one for each case (Ai, Bi, Ci, Di), i ∈ (1, …, 4) that detects the shifting of each case. The result of these 16 neurons gives 16 θi (final vector output) (Fig. 2) with Wi (weight vector) in the second layer are all equal to 1 whereas the Wi of the first layer remains as it stated in the Boolean function algorithm.

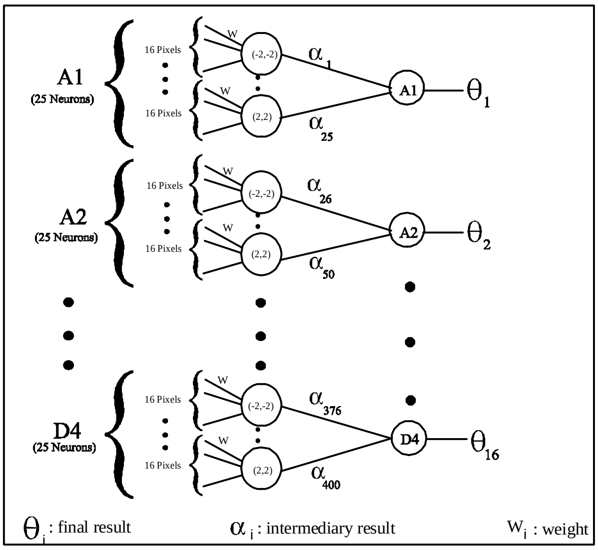

Fig. 2: Second approach

During the training phase for each pattern of the training set the θi with i ∈ (1, …, 16) are computed for all the neurons (Ai, Bi, Ci, Di), i ∈ (1, …, 4). But before we should determine each αi, i ∈ (1, …, 400) is determined for all the neurons (Ai, Bi, Ci, Di), i ∈ (1, …, 4), each αi for one case from A1 to D4.

The equations for neuron A1 are:

$$\theta_1 = \sum_{i=1}^{25} \alpha_i \tag{9}$$

and

$$\alpha_1 = \sum_{1}^{16} Wa1_{(-2,-2)} * A1_{(-2,-2)} \tag{10}$$

.

$$\alpha_{25} = \sum_{1}^{16} Wa1_{(2,2)} * A1_{(2,2)} \tag{11}$$

During the recognising phase each pattern of the test set is compared to all the patterns of the training set. The comparison of one pattern of the training set to one pattern of the training set is as follows:

- compute the Pi (final vector output) with i ∈ (1, …, 16). The equations for Pi are:

$$P_1 = \sum_{i=1}^{25} \beta_i \tag{12}$$

and

$$\beta_1 = \sum_{1}^{16} Wa1''Ent''_{(-2,-2)} * A1''Test'' \tag{13}$$

.

$$\beta_{25} = \sum_{1}^{16} Wa1''Ent''_{(2,2)} * A1''Test'' \tag{14}$$

- comparison of the Pi with θi and compute the number of occurrence K where Pi = θi,
- if K > 12 (fixed threshold) then the pattern is recognised else it isn't.

3. EXPERIMENTAL RESULTS

Before testing the algorithm we have constituted both the training set (Fig. 3) and the test set (Fig; 4). All the patterns constituting either the training set or the test set can be found on many network maps dealing with phone.

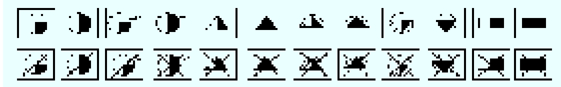

Fig. 3: The training set.

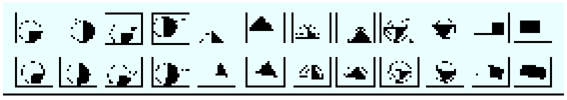

Fig. 4: The test set.

After testing the algorithm we find that the upper limit of recognition of a pattern including rotation is ±10°, the upper limit of recognition of a pattern including black noise is 15% and the upper limit of recognition of a pattern including white noise is 40%. In order to increase the lowest limit of rotation, we have managed to add to the training set 36 times the pattern, each one is rotated by 10°.

4. CONCLUSION

In this paper we have made an improvement of the Boolean function algorithm with two approaches. The limitation of the first approach has lead us to develop a second approach much better than the first one. After testing the algorithm, this latter proved to be suitable for pattern recognition in the field of mapping. Finally, the algorithm can be further improved by extending the limit (16 x 16 pixels) to 256 x 256 pixels.

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