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OPTIMAL CLASSIFICATION USING RBF FOR FACE RECOGNITION

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Abstract: *Classification analysis work performed by radial based function networks (RBF). I watched to obtain a minimum number of incorrect classifications based on image processing using features extraction algorithm using a variable number of pixels in each image analysis.*
I determined the optimal performance for a minimum number of pixels processed and RBF unit for radius. This was achieved by two representations of data: Gaussian function, Euclidean distance and Gaussian function, Manhattan distance.
At the same time I realized and a representation of performance classification by radius, number of RBF units and processing time. Finally we concluded the best efficacy experiment.
Keywords: *Radial based function networks, systems vector machine, support vector number, incorrect classifications, pixels.*

Introduction

Human Face Detection pose much higher than other objects because face detection is a dynamic object that appears in many forms and colors. However, the algorithms of the face detection and tracking of its many advantages. Human-computer interaction could be greatly enhanced by emotion detection, gesture recognition, face tracking and characterization, etc.
An image is only a matrix which is the light intensity of each element in the array is called the pixel. Analysis of these pixels for face detection is time consuming and difficult because of large variations in shape and color of human faces.
There are several algorithms used to detect faces, each with its own strengths and weaknesses. Some algorithms use color tones, some outlines, templates complex neural networks, or filters. All these algorithms involve using an impressive computing power.
I submitted a software implementation of a neural network, which can determine which is best for processing under a small number of input parameters.
We sought to determine the most effective extraction algorithm on the application of patterns, creating a graphical representation thereof.
Also watched and adjusting the parameters in order to improve their algorithms and the ideal solution, and the processing time.
Image recognition is an important source of information based on the idea that people can make different decisions when it comes to rapid data processing.
Comparative analysis performed in the experiments using chaotic image scanning instead of traditional [6], [7]. It runs as a low complexity algorithm, and lead to progressive image compression or discovery swift relevant features of each image separately [8], [9]. In the experiments we used only a very small part of the pixels transmitted.
Getting in a short time the characteristic features an image database used test should be performed without increasing the complexity of the algorithm [10].
The algorithm used in the same area of face recognition has different ways of solving this concept [7]. The practical application has involved a software implementation, to determine which is the best option for extracting facial features with a minimum of iterations, with very little processing time and number of input parameters as low as possible.
Representing experimental data is achieved by tables and graphs that describe the performance of each neural networks studied in this report. We demonstrated how each network parameters affect the optimal solution reached by the algorithm, and how to modify its performance.
I chose datasets that were enough examples to create a sufficiently large test set and obtain statistically significant results.

Model for recognizing facial features using scanning chaotic

Scan the image transmission system is achieved by replacing traditional scanning chaotic one. The result will be a less complex system with encryption transmission and distribution of spectrum used for compressing images [6].
Because recalculation pixel row scan is allowed to form progressive compression and rapid discovery of relevant characteristics of images using only a fraction of the pixels transmitted.
The main component of the proposed system is a chaotic counter based on a cellular automaton

with a pseudo-random behavior which has the property of sync.

Reading images

Database used are specific algorithm [1-4]. The process envisioned involves first part of the algorithm, the actual completion and processing of test images in the database defaults. Follow extracting feature vectors to be used later in the drive. Set the file path from which it starts going through the contents of each file.

It will go through all the images, each image will be read and loaded into a variable. This process will occur for each file that contains images [5].

Training was performed with a database 552 containing images of size 90x120 pixels, a part of which is shown in Figure 2.1.1.

For video broadcasts once the most important consequence of rapid coverage property is the possibility of adapting the transmission rate flexible image content with a very low rate for another scene or part of the image widest accurate time, if movement.

Figure 2.1.1. Photo Selections from the database used

The database was made personal and contains a number of 552 JPEG photos or images of 46 subjects, men and women, young and old, of different ethnicities [3].

Each subject was asked to simulate many emotions that were tagged in the database xyJPEG form or photographic subject number and position where it was photographed.

Database reflect variations in facial expressions of the subjects as normal / neutral, happy, sad and their intermediate states.

The subjects were photographed in these positions, numbered:

1. Normally, the front, eyes open;
2. Normally, front, eyes closed;
3. Normally, side, facing left, looking forward, eyes open;
4. Normally, side, facing left, looking forward, eyes open;
5. Happy, happy, smiling;
6. Sad countenance;
7. Astonished, surprised;
9. Angry frown;
10. With glasses;
11. With cap, hat, scarf (head covering);
12. With glasses and head coverings.

The first part of the algorithm will involves the effective and processing of test images within predefined database and extracting feature vectors to be used later in the drive.

Training

Images will go through a manufacturing process using a function called chao_feature created [5]. This function is a simple algorithm for converting an image into a so-called "feature vector" F predetermined size N (N = 100). F will be in the form of a column vector and contains a number of relevant data for each image part.

Function chao_feature scanning starts from the chaotic first N samples of image scanning from the same point regardless of image used [6].

By converting all the images in the database will create two sets of data: the drive test and that will be used as input for RBF neural network classification step or the analysis of the performance of the algorithm used.

The resulting data will be stored in the two structures called Samples and Labels (which belongs to the class label vector result).

Classification

Stage classification is performed using radial basis functions (RBF).

• A network with radial basis functions (RBF) is an artificial neural network that uses radial basis functions as activation functions.

• It is a linear combination of radial basis functions. They are used in function approximation, time series prediction and control. Coaches are easy systems converge. Cj center vectors are viewed as support vectors, they building benchmarks input space.

Set the file path to which the file starts and scroll way: It will go through all the images, each image will be read and loaded into a variable. This process will occur for each file that contains images.Set the file path to which the file starts and scroll way: It will go through all the images, each image will be read and loaded into a variable. This process will occur for each file that contains images.

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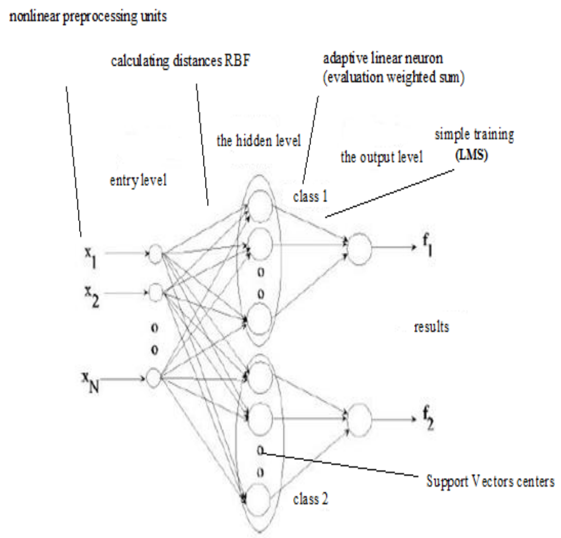

Figure 2.3.1. RBF network architecture

Selection algorithm

Each unit covers a region RBF clear space entry. If an input vector is not covered sufficiently RBF have created a new unit and its associated center will correspond to the new input vector. The algorithm will provide a sequence of integer indices so that all centers are clearly specified input vectors among all the input set. The number of RBF units is determined automatically. It depends on the specific data set radius TR and RBF.

Simulation of RBF networks with fast training algorithm contains the following steps:

a / To define the structure and algorithm parameters drive:

RBF neuron excitation threshold for a radius RBF units, the rate of output layer drive, type RBF function (modified = rbf_dog; Gaussian = rbf_gus; Rectangular 'rbf_rec'), type the distance (Manhattan 'manh' or Euclidean 'Eucla') the number of periods between two successive views (Nmax = 1000;% the maximum number of epochs)

b / Defining the 2 sets of stimuli (training / test) is performed by forming vector stimulus and response, separately for testing and training

c / initialize and test drive contains:

current number of completed time, the number of centers obtained after a time

d / Start drive for another time achieved weights adaptation and preparation for the next step drive

Algorithm "allocation unit" for every new input vector pattern presented sets applied RBF neurons

e / activation rating:

• the issue of whether or not to create a new neuron (if act <threshold); creates a new neuron synapse initialize a new pattern for the set corresponding to RBF proved insensitive; monitors the number of neurons activated;

• evaluates the network output (drive end to an era, for all ages, displaying the drive error, displaying the number of RBF units); views of entrainment results as: title (conducted and proposed); title ('Evolution in drive error'); title ('The number of RBF neurons'); -reînceperea testing operation. The software described in [2].

2.5. Data conversion

Data conversion can be achieved through two functions svm2stand / stand2svm to use the database in the neural network models. These conversion modes linking the output resulting from the extraction of features related to database used as a prototype for analysis and representation of the input data for neural networks.

These functions accept a conversion format RBF network to be introduced as input data in the application. In the process of feature extraction resulting two data fields of training and test in a format different from the neural network. These models were chosen functions to transform data resulting from the extraction of relevant data of the images in the database in a format supported by the network.

When using RBF network type will be used in performance analysis stand2svm conversion function implies a similar algorithm.

In [7] is presented in detail a simple function of converting an image into a vector for extracting facial features, F having a predetermined size N (parameter).

EXPERIMENTAL RESULTS

Epigenice algorithm

This algorithm has been tested for several types of images which sought calculating the ratio of similarity between test picture and pictures from the database using the prototype. To reach conclusions conclusive in this module testing were chosen more and test data were presented to support graphics as well as discussed in the theoretical part.

Case 1:

I used the image of one of the test existing images in the database used to compile this test, shown in the following figure. This should help to determine which of the images in the database used is the degree of similarity with the test image and the highest value is that value.

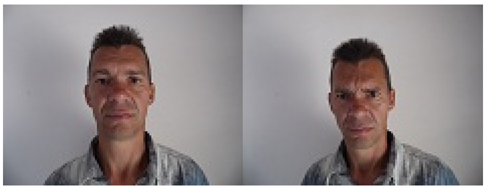

Figure 3.1.1. Photo from personal database used for testing

Case 2:

We chose another picture of test in order to test the algorithm previously well to the theoretical part. We determined after learning algorithm, the greatest degree of similarity between the test image and the images in the selected database.

Figure 3.1.2. Photo from personal database used for testing

To test the incorrect classification is used arhiectura RBFpentru which will change the input parameters from a database of the test taken as a basis to obtain the best possible results.

Chaotic extraction function will use only the image 100 pixels (Ns variable in the program will feature extracting value 100).

Extraction of facial features using scanning chaotic by training a neural network RBF

Experiment when using a data set (Gaussian function, Euclidean distance)

As a first example we used a neural network RBF-M type, and data were stored as a table. I tried changing the input parameter radius RBF unit, in order to obtain the best classification performance.

Table 3.2.1

Variant representation when using a data set (Gaussian function, Euclidean distance)

ray	Number of RBF units	PCIC(%)
1.5	1095	88.7336
2.5	304	84.7039
3	150	87.2533
5	29	93.9967
6	17	95.477

Chaotic extraction function used 100 pixels in the image

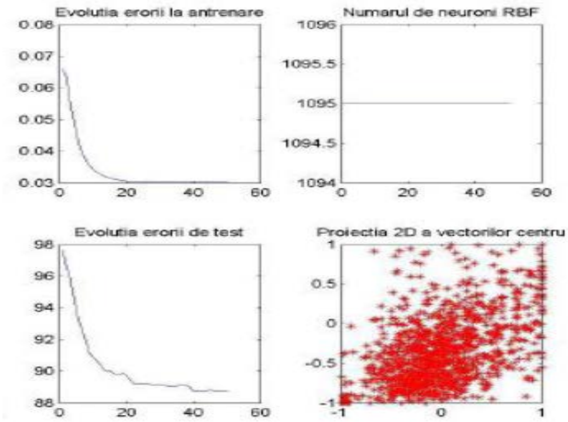

Figure 3.2.1. Representation obtained for radius = 1.5

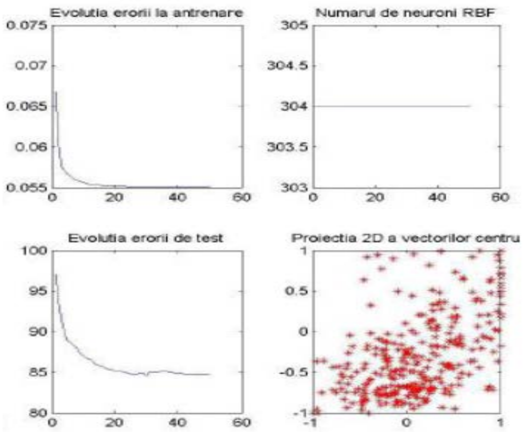

Figure 3.2.2. Representation obtained for radius = 2.5

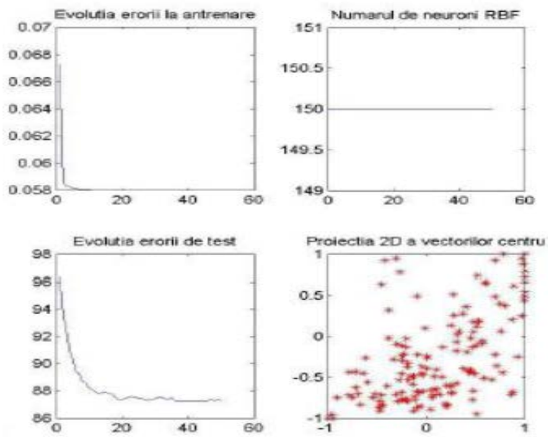

Figure 3.2.3. Representation obtained for the radius = 3

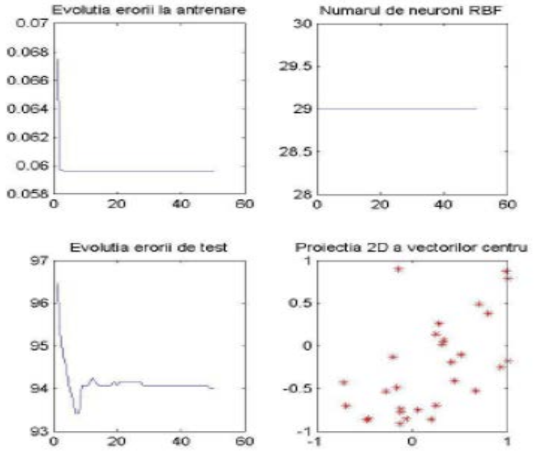

Figure 3.2.4. Representation obtained for the radius = 5

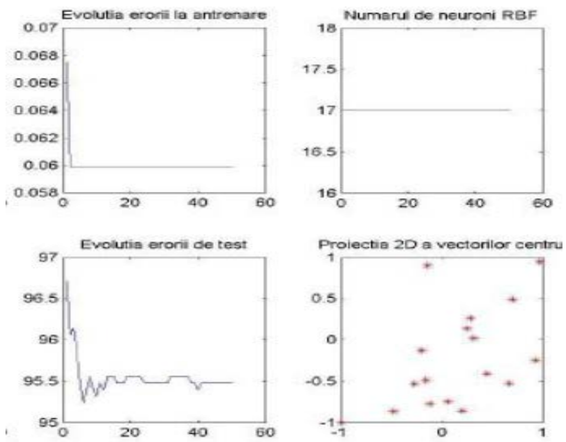

Figure 3.2.5. Representation obtained for the radius = 6

Average processing time in this case falls to 100.084277 seconds.

Extraction of facial features using scanning chaotic by training a neural network RBF

Experiment using a data set (Gaussian function, Manhattan distance)

Table 3.3.2.

Variant for representation when using a data set (depending on type Gaussian and Manhattan distance)

ray	Number of RBF units	PCIC(%)
1,5	1251	96.3816
2.5	1250	96.3816
3	1249	96.2993
5	1244	96.2171
6	1242	96.1349

Chaotic extraction function used 100 pixels in the image

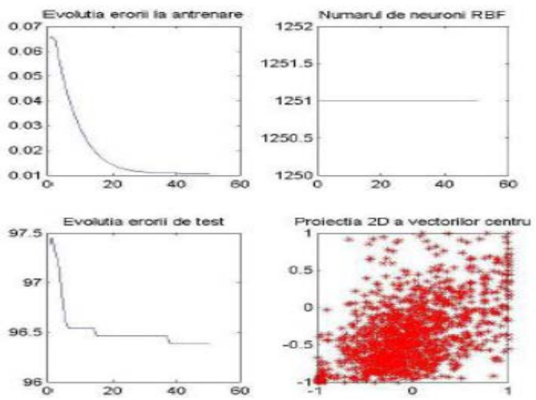

Figure 3.3.1. Representation for radius = 1.5

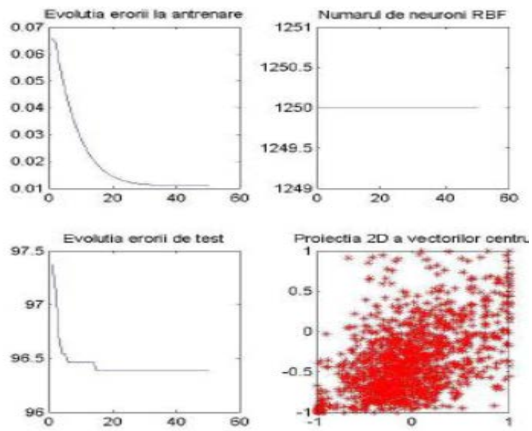

Figure 3.3.2. Representation for radius = 2.5

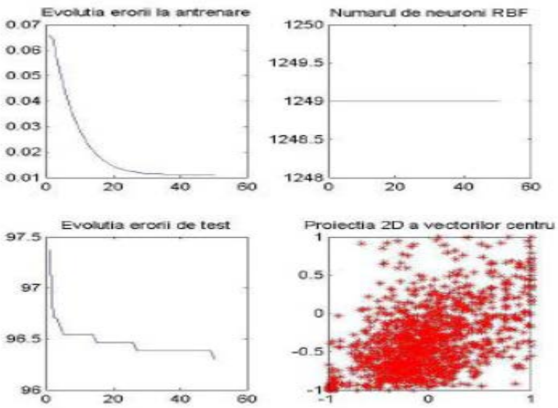

Figure 3.3.3. Representation for the radius = 3

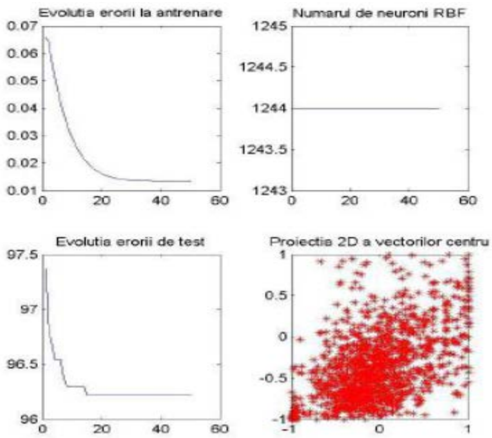

Figure 3.3.4. Representation for the radius = 5

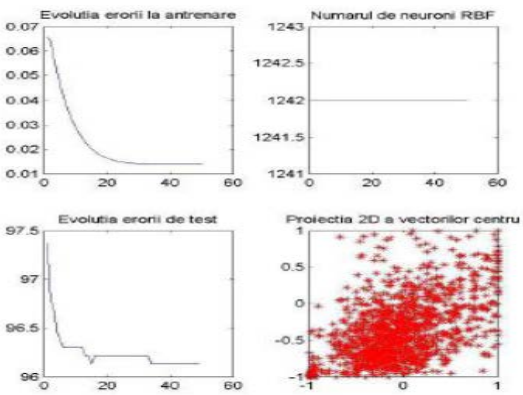

Figure 3.3.5. Representation for the radius = 6

Processing time in this case was very high than in the previous case (1980.442131 s) and also due to the complexity of the calculations to be performed along each side images (manhattan distance calculation is more complex than the distance Euclidean).
Using this procedure, it is recommended to reduce the algorithm complexity and execution time of the method of implementation.

Variant for image representation using 512 pixels.
Particular case
Chaotic feature extraction we used only 512 pixels in the image (Ns variable in the program took extracting features 512 value, and samples from test data or test were chosen at random).
As a first example we used a neural network RBF-M type, and data were stored in a table. Tried changing the input parameter radius RBF unit, in order to obtain the best classification performance.
Function RBF is Gaussian shape, and type is the Euclidean distance. Number of epochs I reduced to 50 (50% compared to the first case) to reduce data processing time.

Table 3.4.1.
The number of incorrect classifications based on RBF unit size range

ray	Number of RBF units	PCIC(%)
1.5	1095	88.7336
2.5	304	84.7039
3	150	87.25
5	29	93.99
6	17	95.477

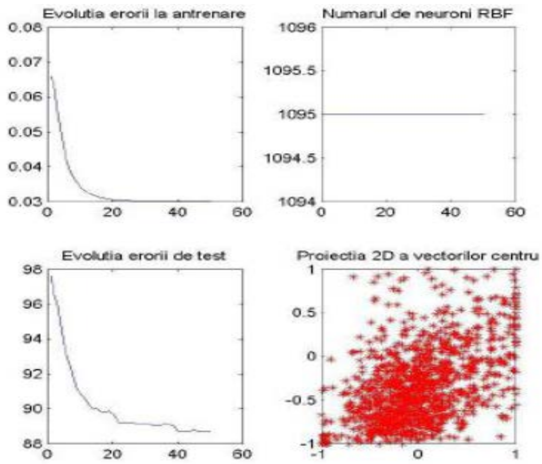

Figure 3.4.1. Representation for radius = 1.5

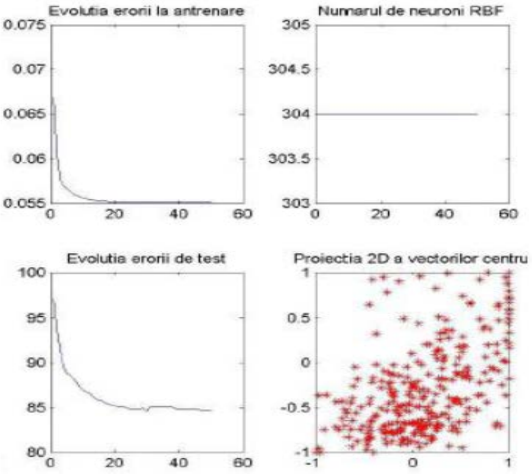

Figure 3.4.2. Representation for radius = 2.5

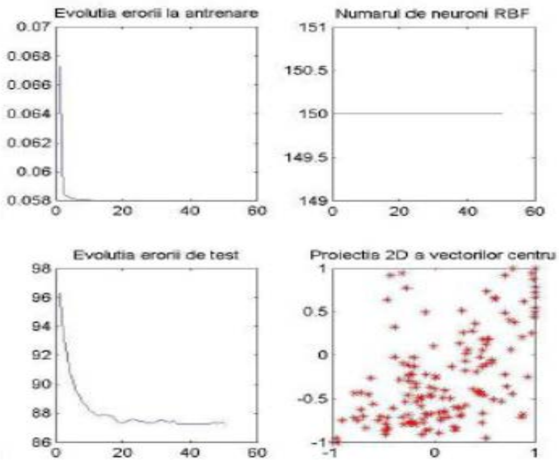

Figure 3.4.3. Representation for the radius = 3

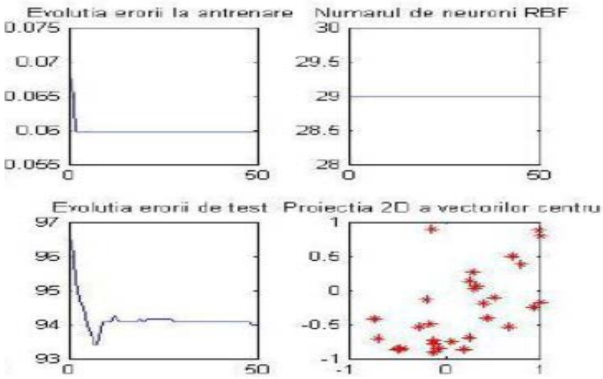

Figure 3.4.4. Representation for the radius = 5

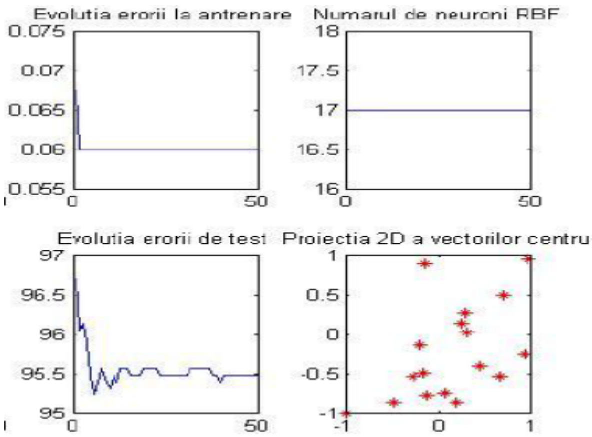

Figure 3.4.5. Representation for the radius = 6

Processing held in 50.021100 seconds

CONCLUSIONS

Optimum performance of RBF neural network model-M to the number of pixels in each image are processed in the database is represented below:

Table 4.4.1.
Optimum performance based on the number of pixels processed images

The number of pixels from image (Ns)	optimal performance (RBF unit ray)
10	87.25(R=3)
50	86.92(R=3)
100	84,7039(R=2.5)
250	86.92(R=2)
400	86.92(R=2)
512	84.70(R=6)

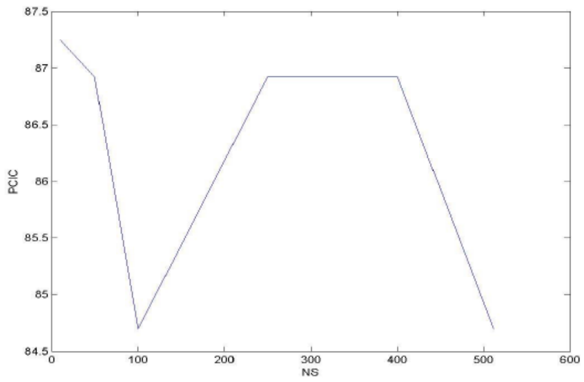

Figure 4.4.1. Graphic with optimal performance based on the number of pixels processed

Table 4.4.2.

Comparison of classification results obtained by the best two representations

Data representation type	The best classification (PCIC%)	Ray	Number of RBF units	Processing time (sec.)
Gaussian function, Euclidean distance	84.7039%	2.5	304	100.084277
Gaussian function, Manhattan distance	96.1349%	6	1242	1980.442131

It is noted that RBF neural network represented by Euclidean distance calculation provides performance processing time of 100 seconds to 1980 seconds Manhattan representation.

The first option that offers the best classification by the smallest function value uncertainty PCIC (84.7039%) than the second (96.1349%).

The number of RBF units are used in the first case 304 units corresponding to a radius of 2.5 and in the second case in 1242 corresponding to a radius of 6 units.

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