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Performance Analysis of the Feedforward and SOM Neural Networks in the Face Recognition Problem

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***Abstract*-This paper presents a comparative study between a feedforward neural network and a SOM network. The paper also proposes the incorporation of a new spatial feature, face feature lines, FFL, to represent the faces. FFL are considered as new features based on previous studies related to face recognition tasks on newborns. Besides the face feature lines, the feature vector incorporates eigenvectors of the face image obtained with the Karhunen-Loeve transformation. A face recognition system is based on a feedforward neural network, FFBP, method. The second classification scheme uses a Self Organized Map, SOM, architecture combined with the *k*-means clustering algorithm. Experiments comparing both architectures show no significant differences for the ORL database, 92% for the FFBP and 90% for the SOM. However results obtained for the Yale database, 60% for the FFBP network and 70% for the SOM, indicate a better performance with the SOM architecture.**

I. Introduction

Face recognition has become a challenge area in pattern recognition and computer vision. There are 30 years of research in this area. This has caused current face recognition systems to have high recognition rates under controlled conditions of illumination, pose or facial expression. However, robust face recognition systems are required in sophisticated security systems. Robustness must be translated into system tolerance to viewpoint, pose, illumination, and facial expression [1]-[21]. We humans recognize thousands of faces learned during our lifetimes. Our visual performance is very robust against changes in a variety of factors: viewpoint, pose, illumination, and facial expression. Yet, we know only very little about how the brain actually solves this task.

Biological neural architectures have taught us several important lessons. The first comes from biologically inspired visual preprocessing in the form of filters that are localized both spatially and in the frequency domain (for example, wavelets, Gabor functions, and Laplacean filters). Two of the most important face recognition methods currently used are the eigenface and Fisherface methods. The eigenface method, or principal component analysis (PCA), is the most well known method for face recognition [22]. PCA is a popular method in image processing and communication theory that is quite often referred to as a Karhunen–Loeve transformation (KLT). The PCA approach exhibits optimality when it is applied to reduce the dimensionality of the feature vector. However, it is not ideal for classification purposes as it retains unwanted variations occurring due to diversified lighting and facial expression [23]. The KLT method is used in this work to map an original feature vector to a new feature space. With the purpose of improving the classic methods for face recognition, neural networks theory is incorporated in this work to generate a new face recognition method. Two different neural networks architectures are study, feedforward and SOM. The purpose of this study is to analyze the performance of the two basic learning schemes, supervised and unsupervised, in the face recognition problem.

In this paper we describe the Hough-KLT algorithm for facial feature extraction in Section 2. Section 3 describes the feedforward neural network classifier case. The SOM architecture is analyzed in Section 4. Finally the general conclusions of this work are presented in Section 5.

II. Face Recognition Through Hough-KLT Features

In this paper we propose a novel approach for face recognition. The method incorporates the visual perception viewpoint. From the perception studies it is noted that some facial features in the space domain like, nose to mouth distance, or geometric shapes like the eyes to mouth shape, are discriminative features between different human been.

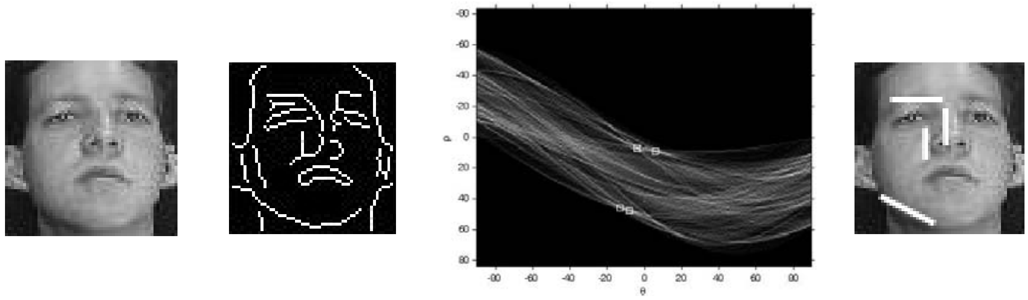
In this paper we propose a new spatial feature named face feature lines, FFL. FFL are prominent lines in low resolution face images, and can be extracted using the Hough transform. These features are important as reported in studies with new born regarding face recognition.

One of the most interesting results is that the facial feature extraction process in newborns is a totally fuzzy task in terms of their vision systems. The babies can only recognize fuzzy facial lines and circles pattern [12]-[13]. This suggests that the use of lines in the face recognition problem is also supported by the psychology and neurology regarding the face perception based on newborns.

A. Face Feature Vector Generation

The Hough transform is a useful transformation to detect geometric patterns in images, like lines, circles, and ellipses. In the domain of the Hough transform, HT, any line is defined by the parametric equation

$$\rho = x\cos\theta + y\sin\theta \qquad (1)$$



a) b) c) d)

Fig.1. Hough transform of a face: a) Original image, b) Face edges, c) Accumulator of the HT. d) Original image plus its four FFL.

where x and y represent the coordinate of a pixel, ρ is the distance of the line to the origin, and θ is the angle of the line with respect the horizontal axis. We can extract the FFL by obtaining the maximum points in the result of the HT through ρ , and θ.

We consider that four face feature lines are enough to represent a face, based on the experiments related to the newborns vision system. These four FFL have shown significant improvement in the performance of fuzzy face recognition systems [24]. The information of these four FFL will be included as components of the feature vector which is defined in detail on further subsections. Application of the HT to a face to locate the four FFL is illustrated in the Fig. 1.

The features vector including the FFL is obtained as follows:

Step 1. Find the four maximum peak values of the lines.
Step 2. Obtain the four characteristic lines coordinates.
Step 3. Encode the coordinates information by taking the value of the first coordinate of the *i*-th line, x_{1i} and add it to $\frac{y_{1i}}{1000}$, and include the result to l_{i_1} .
Step 4. Take the value of the second coordinate of the *i*-th line, x_{2i} and add it to $\frac{y_{2i}}{1000}$, and include the result to l_{i_2} .

The FFL feature vector can be defined as follows

$$\mathbf{z}_i = [l_{i_1} \quad l_{i_2}]$$

$$\mathbf{z}_i = \begin{bmatrix} x_{11} + \frac{y_{11}}{1000}, x_{21} + \frac{y_{21}}{1000} \ldots & \\ & x_{1i} + \frac{y_{1i}}{1000}, x_{2i} + \frac{y_{2i}}{1000} \end{bmatrix} \quad (2)$$

The $\mathbf{z}_i$ vector must be concatenated with the original image $I(x,y)$, in a canonical form (vector column) $\mathbf{i}_{xy}$, to construct the final feature vector

$$\mathbf{x}_{i+xy} = [\mathbf{z}_i \quad \mathbf{i}_{xy}] \quad (3)$$

The vector $\mathbf{z}_i$ is linked to the information of the original image in order to contribute and complement the face information representation before the transformation via KLT.

B. Principal Component Analysis and Karhunen-Loeve Transformation

Principal Component Analysis, PCA, is a very widely used technique for dimensionality reduction. The objective of PCA is to transform the representation space X into a new space Y, in which the data are uncorrelated. The covariance matrix in this space is diagonal. The PCA method leads to find the new set of orthogonal axis to maximize the variance of the data. The final objective is dimensionality reduction of the problem [25].

The steps needed for PCA are the following.

Step 1. The covariance matrix $\mathrm{Cov}_\mathbf{X}$ is calculated over the input vectors set $\mathbf{x}_i$ that corresponds to i facial images represented as vectors $\mathbf{x}$. The covariance is defined as

$$\mathrm{Cov}_\mathbf{X} = \frac{1}{n-1}\sum_{i=1}^{n}\left(\mathbf{x}_i - \bar{\mathbf{x}}\right)\left(\mathbf{x}_i - \bar{\mathbf{x}}\right)^T \quad (4)$$

where $\bar{\mathbf{x}}$ denotes the mean of each variable of the vector $\mathbf{x}$, and n is the amount of input vectors.

Step 2. The *n* eigenvalues of $\mathrm{Cov}_\mathbf{X}$ are extracted and defined as $\lambda_1, \lambda_2, \ldots \lambda_n$, where $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n$.
Step 3. The *n* eigenvectors are $\Phi_1, \Phi_2, \ldots \Phi_n$ and are associated to $\lambda_1, \lambda_2, \ldots \lambda_n$.
Step 4. A transformation matrix, $\mathbf{W}_{PCA}$, is created $\mathbf{W}_{PCA} = [\Phi_1, \Phi_2, \ldots \Phi_n]$.
Step 5. The new vectors $\mathbf{Y}$ are calculated using the following equation

$$\mathbf{Y} = \mathbf{W}_{PCA}^{T}\mathbf{X} \tag{5}$$

where T denotes the transpose of $\mathbf{W}_{PCA}$, and $\mathbf{X}$ denotes the matrix containing all the input vectors.

The KLT is similar to the PCA [26], however in the KLT the input vectors $\mathbf{x}_i$ are normalized to the interval [0,1] before applying the PCA steps.

C. ORL and YALE face databases

The face database "Olivetti Research Laboratory" (ORL), was collected between 1992 and 1994, it has slight variations on pose, illumination, facial expression (eyes open/closed, smiling/not-smiling) and facial details (glasses/no-glasses) [26][27]. ORL has 40 different subjects, where we have used 10 samples per subject. Fig. 2 presents an example of the ORL database.

Fig. 2. Sample faces of the ORL database.

The Yale face database contains images of subjects in a variety of conditions included with/without glasses, illumination and expression variations [26]. We have utilized 10 subjects of this database and 10 samples per subject. In Fig. 3 are presented samples of two different subjects under the conditions described above.

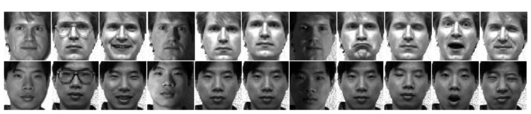


Fig. 3. Sample faces of the YALE database.

III. FFBP-Hough-KLT for Face Recognition

A feedforward network is defined as a computing device where the processing units are distributed on layers in a unidirectional way via weights [28]. In this section we describe the experiments and the results for a feedforward-Backpropagation Hough-KLT face recognition scheme. This scheme is shown in Fig. 4.

A. Feature vector

The feature vector was constructed with (5) under the assumption of $\hat{\mathbf{x}}_{i+xy} = \mathbf{W}_{KLT}^{T}\mathbf{x}_{i+xy}$. The feature vector, as shown in Fig. 4, has an original size of 3408 elements for each single sample. When implementing this kind of huge matrices the complexity of the training algorithms increases according to the size of the matrix. This causes the computers to spend a lot of time making calculations and processes defined by the algorithms. Also this may cause a computer to have insufficient resources. Because of this situation, the feature vector suffered a dimensionality reduction to a size of 34 elements via sub-sampling with the neighbors mean. The dimensionality reduction makes the face recognition problem, more tractable.

The neural network is designed to recognize 10 persons. The network design is accomplished with 8 out of ten available faces of each person. The other two faces are used in the verification stage.

B. Design of the FFBP network

It is known that the architecture of a network of this type is usually determined experimentally, and that is why we do not have a consistent backup for this particular design besides the heuristics.

The experiments realized with this kind of neural network are described next.

The first experiment involves a 2-layer network. The FFBP network was constructed for 34 inputs at the input layer, according to the feature vector size; 80 neurons in the hidden layer according to the number of samples with *tangsig* activation functions; and 10 neurons at the output layer with *purelin* activation functions. The training algorithm used was the Levenberg-Marquardt Backpropagation. For this experiment the performance on design was 98.7% and 50% of correct recognition on design and testing respectively over YALE, and 98.3% 90% for design and testing respectively over ORL.

The second experiment consisted on a 3-layer network. The FFBP network was constructed for 34 inputs at the input layer; 80 neurons in the first hidden layer; 15 neurons in the second hidden layer; and 10 neurons at the output layer with *purelin* activation functions. The network performance achieved was 99% and 60% of correct recognition rate on design and testing respectively for YALE, and 98.8% and 92% of correct recognition for design and testing over the ORL database.

For the third experiment it was utilized the same architecture of the first experiment, but with the Bayesian regularization Backpropagation algorithm. For this architecture the performance on design was 98.9% and 60% of correct recognition on design and testing respectively over the YALE database; for the ORL 99% and 90% of correct recognition was obtained in design and testing respectively.

Other experiments, having the original size of the vector, an input vector of a size of 3408 elements, and also a feature vector of 340 elements, under the previous architectures, results in an intractable problem for this particular approach, due to computational complexity.

C. Testing the FFBP network

The testing phase is performed with one of the two available samples for each person. The sample is picked randomly.

As said before, in several experiments, the computer complexity added by the high dimensionality of the feature vector samples, and the memory limitations of the computers, made the training an expensive task in terms of computational

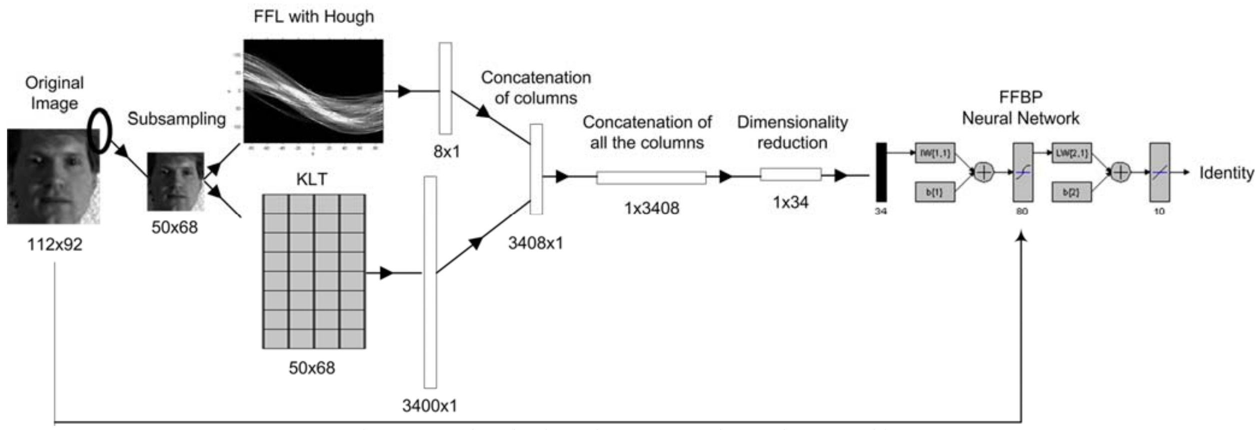


Fig. 4. General work scheme for FFBP-Hough-KLT face recognition.

resources. This has caused failures. As can be shown in Table 1, some of these experiments have failed because of the complexity of the algorithms. This makes us to consider a dimensionality reduction of the feature vector with other methods and techniques. Kernel methods or Data Mining methods are suggested. The summary of all the results for the FFBP network experiments, including the failed experiments are shown in Table 1.

TABLE 1.
SUMMARY OF TESTING EXPERIMENTS FOR FFBP OVER YALE

Experiment	BP Algorithm	Learn	Architecture	Size of Feature Vector	Results Design & Testing
1	TRAINLM	LEARNGDM	34, 80, 10	34x80	98.7%, 50%
2	TRAINLM	LEARNGDM	34, 80, 15, 10	34x80	99%, 60%
3	TRAINBR	LEARNGDM	34, 80, 10	34x80	98.9%, 60%
4	TRAINBR	LEARNGDM	34, 80, 10	3488x80	TOO COMPLEX
5	TRAINBR	LEARNGDM	34, 80, 10	348x80	TOO COMPLEX
6	TRAINLM	LEARNGDM	34, 80, 10	3488x80	TOO COMPLEX
7	TRAINLM	LEARNGDM	34, 80, 10	348x80	TOO COMPLEX
8	TRAINBR	LEARNGDM	34, 80, 50, 10	30x80	TOO COMPLEX
9	TRAINBR	LEARNGDM	34, 80, 15, 10	30x80	TOO COMPLEX
10	TRAINBR	LEARNGDM	34, 34, 15, 10	30x80	TOO COMPLEX

TABLE 2.
SUMMARY OF TESTING EXPERIMENTS FOR FFBP OVER ORL

Experiment	BP Algorithm	Learn	Architecture	Size of Feature Vector	Results Design & Testing
1	TRAINLM	LEARNGDM	34, 80, 10	34x80	98.3%, 90%
2	TRAINLM	LEARNGDM	34, 80, 15, 10	34x80	98.8%, 92%
3	TRAINBR	LEARNGDM	34, 80, 10	34x80	99%, 90%
4	TRAINBR	LEARNGDM	34, 80, 10	3488x80	TOO COMPLEX
5	TRAINBR	LEARNGDM	34, 80, 10	348x80	TOO COMPLEX
6	TRAINLM	LEARNGDM	34, 80, 10	3488x80	TOO COMPLEX
7	TRAINLM	LEARNGDM	34, 80, 10	348x80	TOO COMPLEX
8	TRAINBR	LEARNGDM	34, 80, 50, 10	30x80	TOO COMPLEX
9	TRAINBR	LEARNGDM	34, 80, 15, 10	30x80	TOO COMPLEX
10	TRAINBR	LEARNGDM	34, 34, 15, 10	30x80	TOO COMPLEX

Analysis of the Table 1 and the Table 2 shown that the use of different kind of BP algorithms like the Bayesian Regularization and the Levenberg-Marquardt have shown no significant difference on the results on testing. Also these tables yield important information related to FFBP networks aimed to be used in real time face recognition systems. In the experiments 8 to 10 in both Table 1 and Table 2 it is noted that regardless the feature vector reduction, the systems seems to be expensive in terms of computational complexity. This is caused by the network architecture proposed in these experiments, and also by the learning algorithm. Finally, as expected the highest performance is achieved on the ORL database.

IV. SOM-HOUGH-KLT FOR FACE RECOGNITION

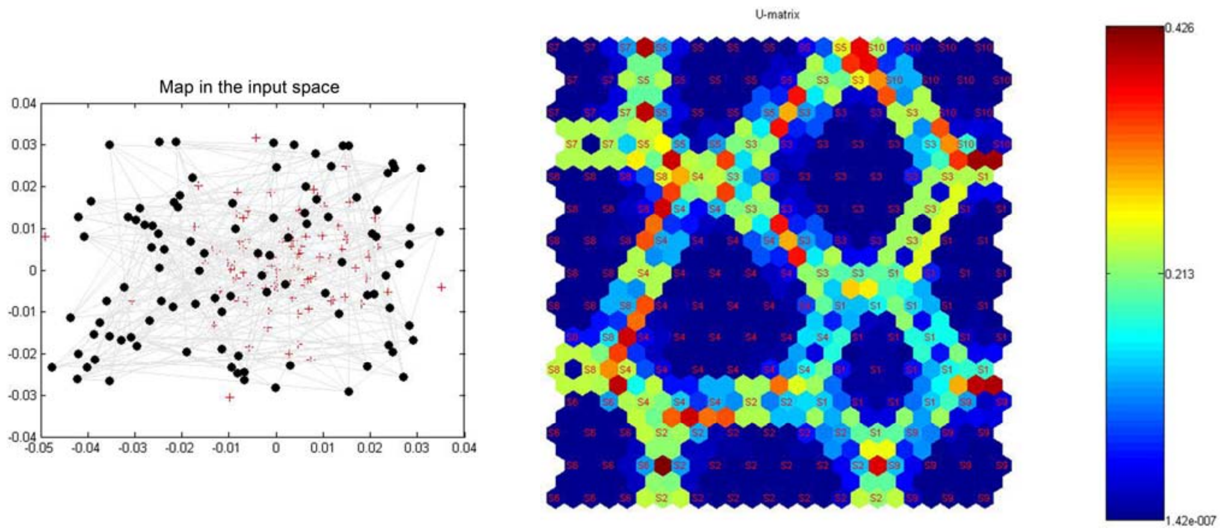
In this section we present the same issue of face recognition using Hough-KTL and FFL as features, but now faced with Self Organizing Maps, SOM.

A. Feature vector

The feature vector was constructed with (5). The face samples picked for training were 8 samples per subject. The samples picked were the first 8 samples of each individual. We have designed the system for 10 people (10 classes). The training matrix size was 3408x80. The face databases utilized are the ORL and the YALE.

B. SOM network design

It is known that the architecture of a SOM network is trained by a non-supervised algorithm [28]. In order to improve the final performance of the SOM, besides training the SOM with the Kohonen algorithm, the *k*-means algorithm is included in the design. The *k*-means algorithm is utilized in pattern recognition to reinforce groups or clusters. The SOM creates a map that tries to represent the input patterns. This map is shown in Fig. 5 a). Once the map is created, the *k*-means algorithm is applied to the map, in order to reinforce the clusters. The *k*-means is applied trying to find 10 clusters, one for each class. Graphical representations of the clusters generated are shown in Fig.5b. Each hexagon in Fig.5b



a) b)

Fig. 5. The final map after Kohonen's training algorithm over ORL is shown in a). b) U-matrix of the SOM map when the *k*-means is applied over ORL.

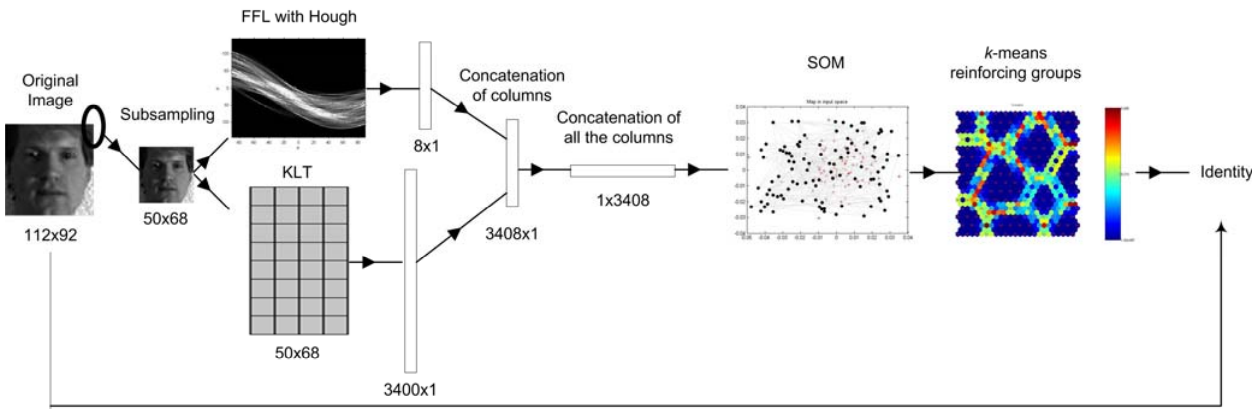


Fig.6. General work scheme for the SOM-Hough-KLT face recognition method.

includes the label corresponding to the subject that has been assigned to a specific neuron on the map. The gray scale represents the clusters found when the SOM is trained with 8 samples per subject. The performance achieved for the ORL was 100% and 90% for design and testing respectively. For the YALE database the performance achieved was 100% and 70% for design and testing respectively. The general work scheme for the SOM-Hough-KLT proposed method is shown in Fig. 6. The U-matrix is a class distribution for graphic representation. The parameters of the SOM with the Kohonen algorithm are shown in Table 3.

C. Testing the SOM network for ORL and YALE databases

For the testing phase, we selected one of the two available samples for testing for each person. The sample selected is the first available. After the first test, the SOM is tested with the second sample. The performance reached on the ORL database with this experiment was 90%, as shown in Table 4. The use of the *k*-means-clustering algorithm, that reinforces the grouping, may justify this higher recognition rate. The performance reached on the YALE database was is 70%, as shown in Table 5. As expected, the performance has lower rates on the YALE database because of the variations in lighting conditions of the YALE database. However the performance is comparable with current face recognition systems based on PCA which achieves 77%.

V. CONCLUSIONS

This paper presented the Principal Component Analysis as a useful tool for feature vector dimension reduction, as well as the KLT. The paper also described the feedforward back propagation scheme for face recognition called FFBP-Hough-KLT. The highest recognition rate on testing reaches 60% on the YALE database. Over the ORL database the performance was 92%. The performance is shown in Table 6. We have implemented dimensionality reduction in some of the methods presented on this document. However, when dimensions are reduced, the performance decreases as well. This suggests more experimentation on dimensionality reduction without loss of information. The paper also described experiments with the SOM approach for face recognition, called SOM-Hough-KLT. The SOM is utilized with the *k*-means algorithm to improve the recognition rate. The highest rate obtained for the ORL database was 90%. For the YALE database the best performance was 70%. The results obtained in this work are comparable to PCA, LDA, FLDA methods. For the YALE database the highest performance reported in the literature analyzed is 80% and for ORL database is 97%.

Another important result is that the SOM network improved with the *k*-means performed better than the FFBP network. This leads us to think that hybrid systems will offer new alternatives to design robust face recognition systems.

TABLE 3
PARAMETERS OF THE SOM AFTER KOHONEN TRAINING

Variable	Value
INPUT DIMENSION	3488
MAP GRID SIZE	15 X 13
LATTICE TYPE (RECT/HEXA)	HEXA
SHAPE (SHEET/CYL/TOROID)	SHEET
NEIGHBORHOOD TYPE	GAUSSIAN

TABLE 4.
PERFORMANCE OF THE SOM ON THE ORL DATABASE

Sample	Training	Testing
1st	100%	90%
2nd	100%	90%

TABLE 5.
PERFORMANCE OF THE SOM ON YALE DATABASE

Sample	Training	Testing
1st	100%	70%
2nd	100%	70%

TABLE 6.
PERFORMANCE SUMMARY

FFBP		SOM	
ORL	YALE	ORL	YALE
92	60%	90	70%

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