Face Recognition Based on Human Visual Perception Theories and Unsupervised ANN

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1. Introduction

The face recognition problem has been faced for more than 30 years. Although a lot of research has been done, much more research is and will be required in order to end up with a robust face recognition system with a potential close to human performance. Currently face recognition systems, FRS, report high performance levels, however achievement of 100% of correct recognition is still a challenge. Even more, if the FRS must work on non-cooperative environment its performance may decrease dramatically. Non-cooperative environments are characterized by changes on; pose, illumination, facial expression. Therefore FRS for non-cooperative environment represents an attractive challenge to researchers working on the face recognition area.

Most of the work presented in the literature dealing with the face recognition problem follows an engineering approach that in some cases do not incorporate information from a psychological or neuroscience perspective. It is our interest in this material, to show how information from the psychological and neuroscience areas may contribute in the solution of the face recognition problem. The material covered in this chapter is aimed to show how joint knowledge from human face recognition and unsupervised systems may provide a robust alternative compared with other approaches.

The psychological and neuroscience perspectives shows evidence that humans are deeply sensible to the face characteristic configuration, but the processing of this configuration is restricted to faces in a face-up position (Thompson, 1980), (Gauthier, 2002). This phenomenon suggests that the face perception process is a holistic configurable system.

Although some work has been done in these areas, it is still uncertain, how the face feature extraction processes is achieved by a human being. An interesting case is about newborn face feature extraction. Studies on newborns demonstrate that babies perceive a completely diffuse world, and their face perception and recognition is based on curves and lines from the face (Bower, 2001), (Johnson, 2001), (Nelson, 2001), (Quinn et al., 2001) and (Slater A. & Quinn, 2001).

Nowadays, there exists some research work on face recognition that has intended to incorporate psychological and neuroscience perspectives (Blanz & Vetter, 2003), (Burton et

al., 1999). However, the solution to the face recognition problem is stated only on bases of matrix operations and general pattern recognition methodologies, without considering other areas as visual perception.

On the engineering area, patter recognition systems approaches offer a large variety of methods. In recently years, unsupervised systems have provided a new paradigm for the pattern recognition problem (Chacon & Ramirez, 2006a). These systems allow data mining or data discovering information that traditional pattern recognition systems do not incorporate. This feature makes it possible to find information in the feature vectors that may not be considered in traditional pattern recognition approaches.

Based on these points, we present in this chapter a new face recognition approach taking into account recently face perception theories and an unsupervised classifier in order to improve the performance of the FRS in non-cooperative environments.

2. Literature analysis

This section presents a survey of 30 representative papers published in recently years. The purpose of this analysis is to provide the reader with a flavor of the variety of paradigms used in the face recognition problem, and to propose a method to compute an index performance of such methods. Table 1 shows the 30 published works analyzed. The numbers on the column No. are used later as references in figures and tables.

The first analysis shown in Table 2 is the robustness of the method with respect to variations on face; **P**ose, **I**llumination, **E**xpression and / or **R**otation. We can observe from Table 2 that only one method assumes tolerance to PIE/R, five of the methods are tolerant to PIE, eight only consider robustness to two variations. Eight methods are designed to be invariant to only one variation, and eight methods are not tolerant to any variation. The most considerable change in the works is **E**, followed by **P**, **I**, and the less is **R**. The performances reported vary from good, No. 1, to very poor No.5.

Figure 1 illustrates the feature extraction methods used in these papers, and Figure 2 shows the type of classifier used. The feature extraction methods are 3D models, Fisher´s Linear Discriminant FLD, Discrete Cosine Transform DCT, Linear Discriminant Analysis LDA, Principal Component Analysis PCA, wavelet based, Bayesian and other methods. It was observed that feature extraction methods that represent data in sub-spaces are the most commonly used. Among the classifier methods the Euclidean distance is the most used, followed by other methods, and the artificial neural network method approach.

With respect to the data bases, ORL, YALE, AR and MIT, are among the most used data bases. The ORL data base presents variations on pose, illumination, and expression (Li & Jain, 2004), (Samaria & Harter, 1994), (Olivetti, 2006). YALE has face images with individuals in different conditions, with and without glasses, changes in illumination, and expression (Li & Jain, 2004), (Yale, 2002). The AR data base includes changes on facial expression, illumination, and occlusion (Li & Jain, 2004), (Martinez & Benavente, 1998). The MIT data base is composed of face images involving variations on pose, illumination and facial expression (Weyrauch et al., 2004). Some examples of these data bases are shown in Figure 3.

No.	Publication
1	Deformation analysis for 3d face matching (Lu & Jain, 2005)
2	Discriminative common vectors for face recognition (Cevikalp et al., 2005)
3	Face recognition using laplacianfaces (He et al., 2005)
4	High-Speed face recognition based on discrete cosine transform and rbf neural networks (Er et al., 2005)
5	Locally linear discriminant analysis for multimodal distributed classes for face recognition with a single model image (Kim & Kittler, 2005)
6	Wavelet-based pca for human face recognition (Yuen, 1998)
7	Real-time embedded face recognition for smart home (Zuo & de With, 2005)
8	Acquiring linear subspaces for face recognition under variable lighting (Lee & Kriegman, 2005)
9	Appearance-Based face recognition and light-fields (Gross et al., 2004)
10	Bayesian shape localization for face recognition using global and local textures (Yan et al., 2004)
11	A unified framework for subspace face recognition (Wang & Tang, 2004)
12	Probabilistic matching for face recognition (Moghaddam & Pentland, 1998)
13	Face recognition based on fitting a 3d morphable model (Blanz & Vetter, 2003)
14	Face recognition using artificial neural network group-based adaptive tolerance (gat) trees (Zhang & Fulcher, 1996)
15	Face recognition by applying wavelet subband representation and kernel associative memory (Zhang et al., 2004)
16	Face recognition using kernel direct discriminant analysis algorithms (Lu et al., 2003)
17	Face recognition using fuzzy integral and wavelet decomposition method (Kwak & Pedrycz, 2004)
18	Face recognition using line edge map (Gao & Leung, 2002)
19	Face recognition using the discrete cosine transform (Hafed & Levine, 2001)
20	Face recognition system using local autocorrelations and multiscale integration (Goudail et al., 1996)
21	Face recognition using the weighted fractal neighbor distance (Tan & Yan, 2005)
22	Gabor-Based kernel pca with fractional power polynomial models for face recognition (Liu, 2004)
23	Gabor wavelet associative memory for face recognition (Zhang et al., 2005)
24	N-feature neural network human face recognition (Haddadnia & Ahmadi, 2004)
25	GA-Fisher: a new lda-based face recognition algorithm with selection of principal components (Zheng et al., 2005)
26	Kernel machine-based one-parameter regularized fisher discriminant method for face recognition (Chen et al., 2005)
27	Generalized 2d principal component analysis (Kong et al., 2005)
28	Face detection and identification using a hierarchical feed-forward recognition architecture (Bax et al., 2005)
29	Nonlinearity and optimal component analysis (Mio et al., 2005)
30	Combined subspace method using global and local features for face recognition (Kim et al., 2005)

Table 1. List of analyzed references.

No.	1	2	3	4	5	6	7	8	9	10
P	✓		✓		✓				✓	✓
I	✓		✓	✓				✓		
E	✓		✓	✓						
R										
%Rec.	91.00	98.34	91.96	91.20	53.00	-	95.0	98.82	70.65	93.66
No.	11	12	13	14	15	16	17	18	19	20
P			✓					✓		
I			✓				✓	✓	✓	
E			✓				✓	✓		✓
R									✓	
%Rec.	96.0	89.5	82.70	-	91.20	-	99.24	73.30	84.58	95.00
No.	21	22	23	24	25	26	27	28	29	30
P	✓	✓			✓		✓	✓		
I	✓				✓	✓			✓	
E	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R	✓									
%Rec.	67.40	95.30	99.30	99.50	89.63	92.03	95.48	79.00	93.00	97.00

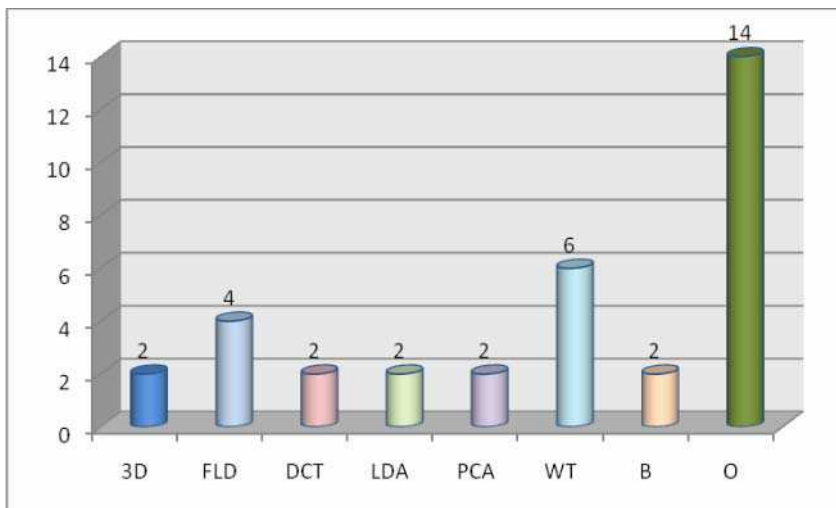Table 2. Robustness analysis with respect to Pose, Illumination, Expression, and Rotation.

Fig. 1. Feature extraction methods. 3D models, Fisher´s Linear Discriminant, Discrete Cosine Transform, Linear Discriminant Analysis, Principal Component Analysis, Wavelet Transform, Bayesian methods, other methods.
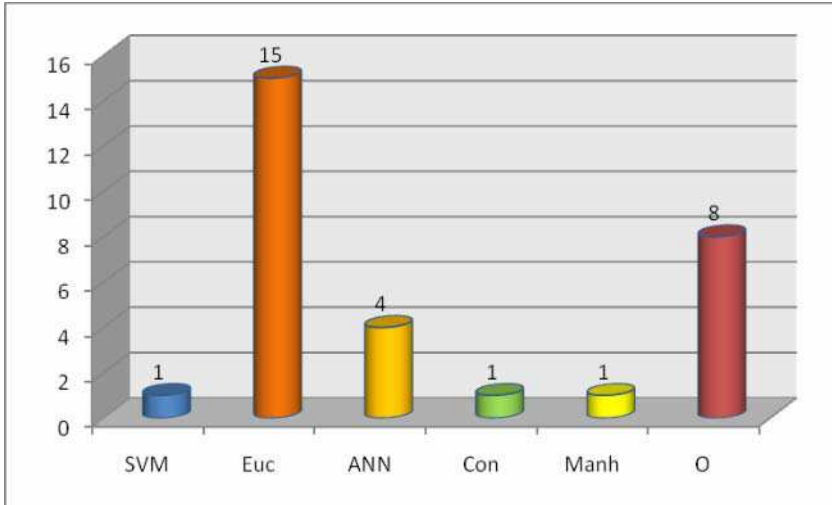
Fig. 2. Analysis by classifier scheme. Support Vector Machine, Euclidean distance, Artificial Neural Networks, Convolution , Manhattan, Other.

Since the experimentation to obtain the performance of the proposed method in the analyzed works is different, it is difficult to achieve a comparison among the methods. Therefore, in order to obtain a comparable performance index we proposed one. The proposed performance index assigns a weight of 10 to the number of individual that can be recognized by the system and a weight of 90 to the recognition performance. These weights were assumed arbitrarily and can be adjusted to a particular criterion. The performance index is defined as follows. Let $p_{\max}$ be the maximum recognition performance of FRS and $prec_k$ the recognition of the $k-th$ method in its different performances. Let also $n_{\max}$ be the maximum number of faces that the $k-th$ method can recognize. $nfaces_k$ is the number of individuals that the $k-th$ method can recognize for $k=\{1,2,3,...,N\}$. Then the performance index is given by

$$p_{\max} = \max\left(prec_k\right), \qquad p_{\max} < 100 \tag{1}$$

$$n_{\max} = \max\left(nfaces_k\right) \tag{2}$$

$$r_k = \frac{prec_k \times p_{\max}}{w_{prec}} + \frac{nfaces_k \times n_{\max}}{w_{nfaces}} \tag{3}$$

where r_k is the proposed performance index of the $k-th$ method. w_{prec} is the facial recognition performance weight, and w_{nfaces} the weight for the number of individuals that can be recognized. Using this performance index, the best method is the $k-th$ method that maximizes

$$d_{\max} = \max\left(r_k\right) \tag{4}$$
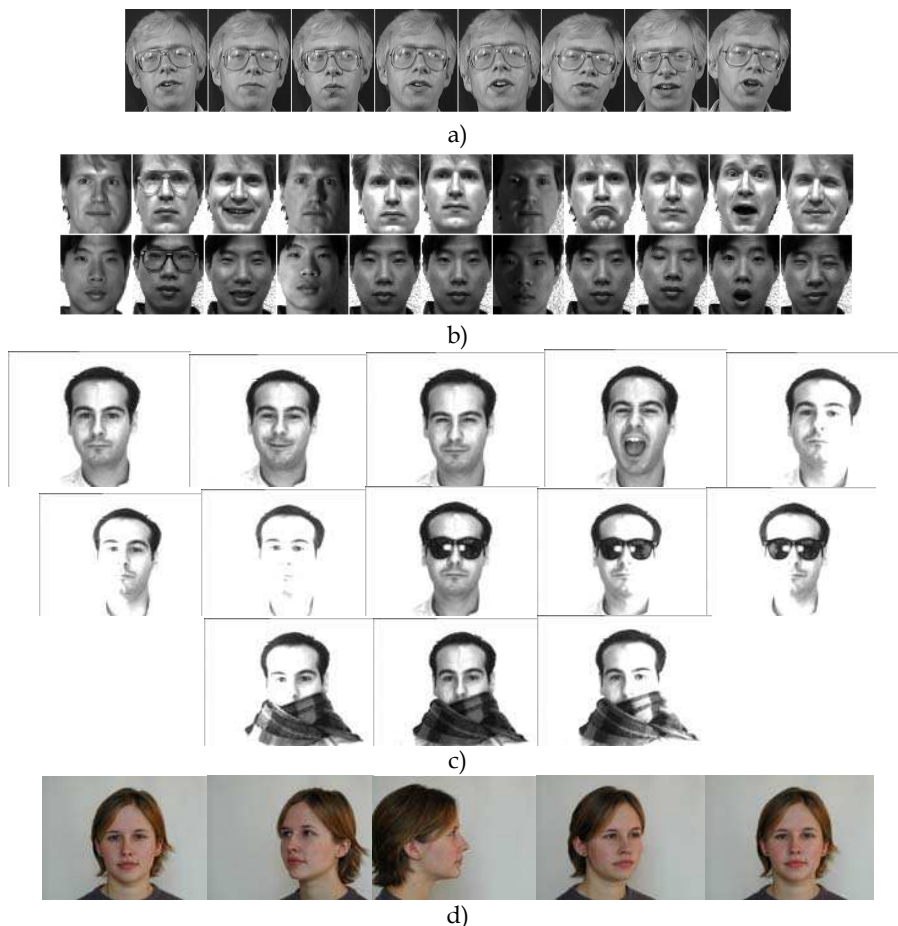
a)

b)

c)

d)

Fig. 3. Example of data base images. a) ORL, b) YALE, c) AR, and d) MIT.

Fig. 4. shows the summary of the performance of the best three methods for each combination of robustness. In Figure 4, the bars indicate the recognition performance for each method, and the lines indicate the number of faces that each method can recognize.

It can be noticed that the performance of the method increases as the number of faces decreases and vice versa. It can also be observed that the methods No. 22 (Liu, 2004), No. 17 (Kwak & Pedrycz, 2004) and No. 3 (He et al., 2005) appear like best methods in more than one robustness category.

A summary of the two best methods is shown in Table 3. It shows the classifier type, and the face feature extraction method used. The best method tolerant to PIE has a performance of 91.96%. From Table 3 it is observed that methods that appear more frequently among the best face feature extraction are based on wavelets. It is also noticed that most of the methods are baseed on simple classifiers like nearest-neighbor, which open the opportunity to investigate with other classifiers like support vector machine, and artificial neural networks in order to improve their performance.
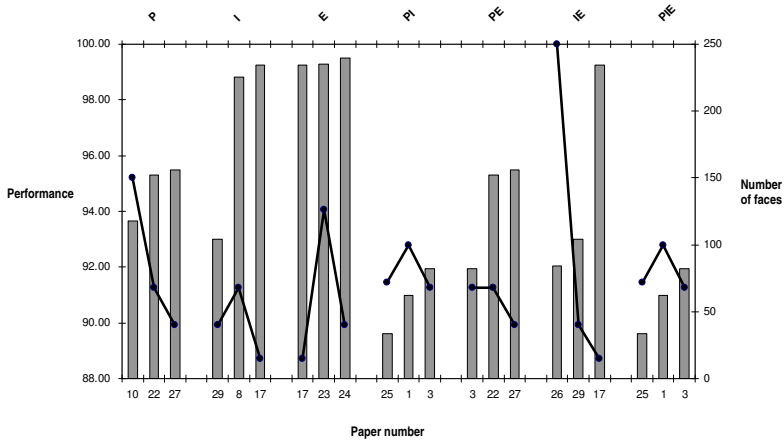
Fig. 4. General results of the evaluation. Bars indicate the percentage of performance. Black lines indicate the number of individual that the method can recognize.

Tolerant to	No.	Classifier	Characteristics
P	10	Euclidian distance	Gabor wavelet representation y Bayesian Shape Localization
P	22	Nearestneighbor using Euclidean distance	Gabor wavelet representation of face images and the kernel PCA method
I	8	9 illumination points(9PL)	9 illumination points(9PL)
I	17	Euclidian distance and fuzzy integral	Wavelet decomposition, Fisherface method
E	23	GWAM	Gabor wavelet associative memory GWAM
E	24	RBF Neural Network	Ellipse of a facial image
PI	1	SVM	Deformation analysis of a 3D figure
PI	3	Nearestneighbor using Euclidean distance	The Laplacianfaces are obtained by finding the optimal linear approximations to the eigenfunctions of the Laplace Beltrami operator on the face manifold
PE	22	Nearestneighbor using Euclidean distance	Gabor wavelet representation of face images and the kernel PCA method
PE	27	Nearest-neighborhood	K2DPCA
IE	17	Euclidian distance and fuzzy integral	Wavelet decomposition, Fisherface method
IE	26	RBF kernel function	K1PRFD algorithm
PIE	3	Nearestneighbor using Euclidean distance	The Laplacianfaces are obtained by finding the optimal linear approximations to the eigen functions of the Laplace Beltrami operator on the face manifold
PIE	25	Optimal projection matrix of GA-Fisher	GA-Fisher

Table 3. Summary of the two best methods.

At this point, we have presented an analysis of reported work on FRS considering, robustness, features used and type of classifiers. In the next section, we present important results on human face perception theory that can be considered in the design of new FRS.

3. Human facial perception theory

Notwithstanding the tremendous effort to solve the face recognition system, it is not possible yet, to have a FRS that deploys effectively in unconstrained environments, tolerant to illumination, rotation, pose, expression, noise, and viewing distance. The most efficient system without any doubt is the human system, therefore, it makes sense to try to discover the secret of this system.

There are some studies in the fields of psychology and neuroscience related to face recognition (Thompson, 1980), (Gauthier & Tanaka, 2002), (Haxby et al., 2001), (Kalocsai, 1998), (Bower, 2001), (Mareschal & Thomas, 2006). However, aside from the diversity of experiments and approaches, it is notorious that there is not a final conclusion about questions like; What features does the brain use to recognize a face?, Is there a specialized region of the brain for face recognition?. From the psychological and neuroscience point of view there exists evidence that humans are very sensible to face configuration, that is, relationship among the face constituents, nose, mouth, eyes, etc. But, the process is related only to upright faces (Thompson, 1980), (Gauthier & Tanaka, 2002). This phenomenon is known as the "Margaret Thatcher Illusion", (Sinha, 2006) and (Thompson, 1980). Figure 6 illustrates this phenomenon. Apparently the brain does not perceive differences between a modified upright face and a normal face, Figures 6a and 6b. This is because for the brain it is easier to process an inverted face. However, when the face that apparently does not have differences in comparison with the normal face is rotated, we can perceive the differences between these two faces, Figure 6c and 6d. This phenomenon indicates that it is possible that face perception is a holistic – configural system, or configuration based.
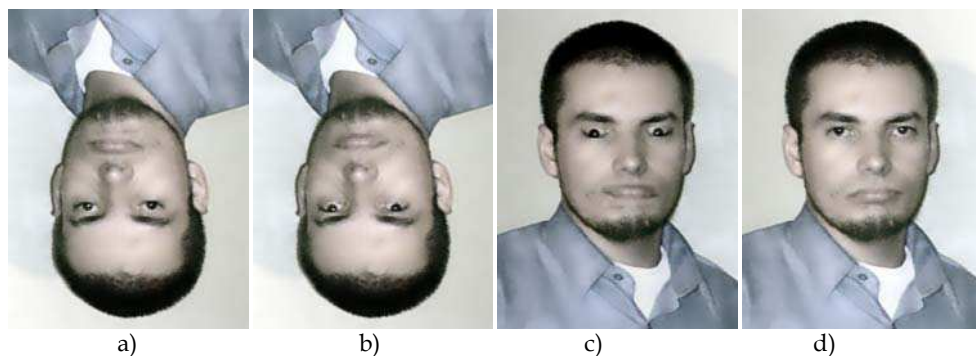

a)   b)   c)   d)

Fig. 6. Examples of the "Margaret Thatcher Illusion". a) Upright face with eyes inverted, b) normal upright face, c) and d) corresponding right faces of a) and b)

The work in (Gauthier & Tanaka, 2002) distinguish between two concepts; holistic – inclusive and holistic – configural. Holistic – inclusive is defined as the use of a part of an object even though it is said to be ignored. On the other hand, holistic – configural is defined as the use of relations among the parts of the object. Therefore, under a holistic – configural approach it is important to consider those relationships to achieve a good recognition performance.

In other studies, the area of neuroscience has suggested that the face recognition process is achieved in the brain by a specialized region (Thompson, 1980), (Haxby et al., 2001). These studies are based on analysis of PET and MRI images during object and face recognition experiments by humans. The *laterar fusiform gyrus* or *Fusiform Face Area*, region shows activity during the face recognition task, but this activity is not detected during object recognition (Kanwisher, 1997), (Tong et al., 2000).

Other evidence suggests a specific region in the brain related to the face identification that is related to the disease called *prosopagnosia*. People with this problem can recognize objects and face expressions but not faces.

Notwithstanding all this research it is not possible yet, to define a coherent theory for the face recognition process in humans. Nevertheless, some works, (Haxby et al., 2001), (Kanwisher, 2006), (Kalocsai, 1998), can state guidelines that can improve the performance of computer FRS. For example the work in (Bower, 2001) indicates that newborns perceive a fuzzy world and they resort to line and curve face shapes for face recognition. Figure 7 illustrates the perception and visual sharpness of newborns during their development (Brawn, 2006). The sequence is Figure 7a newborn, 7b four weeks, 7c eight weeks, 7d three months, and 7e six months. The work in (Peterson & Rhodes, 2003) demonstrates that lines are better features in the holistic configuration to provide discrimination among other type of geometric objects. This could lead to the fact of why newborns have the ability to recognize people using diffuse lines features.
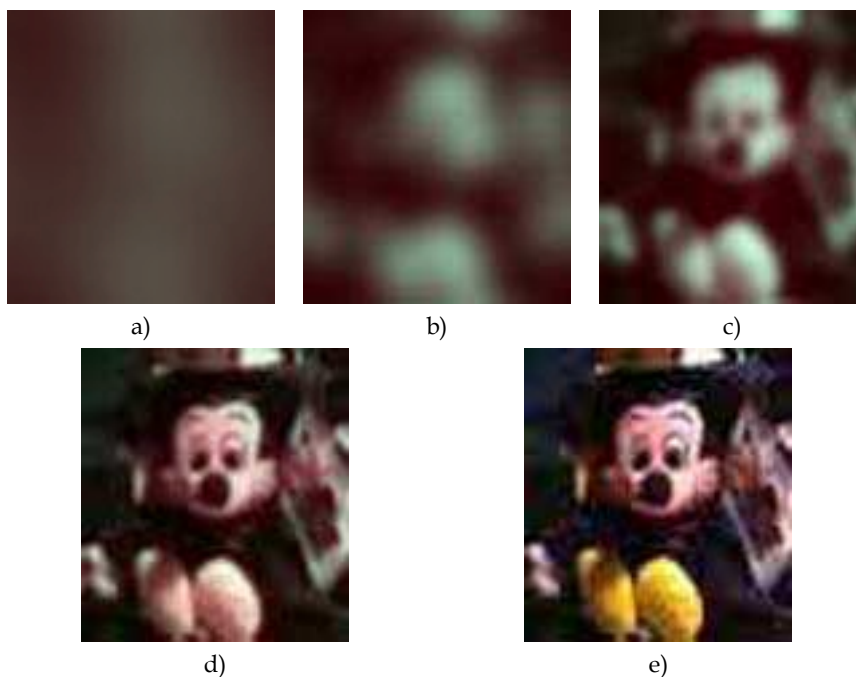

Fig. 7. Newborn visual perception variation. a) Newborn, b) 4 weeks, c) 8 weeks, d) 3 months, e) 6 months. From professor Janice Brown's class presentations (Brawn, 2006).

As a conclusion of this section we recommend the work reported by Sinha (Sinha et al., 2006), where the reader could find nineteen important points a computer vision research interested on face recognition should consider in FRS design. Among those points we can mention; human recognize familiar faces in very low resolution images, high – frequency information by itself is insufficient for good face recognition performance, facial features are processed holistically, pigmentation cues are at least as important as shape cues.

These points are results of human visual perception experiments that are related to the main idea presented in this section, and more details can be found in that reference.

4. Face feature lines, hough-KLT human facial perception theory

Considering the theories presented in section 3 we decided to implement a face recognition scheme based on facial features containing information of the most prominent lines in low resolution faces. Besides the perceptual justification of this theory, an engineering justification to use features lines are the works reported in (Zhao et al., 2003) where lines are combined with PCA and (Konen , 1996), where the ZN-Face algorithm is able to compare drawing faces against gray scale faces using lines. Besides, other works show the advantages, like representation simplicity (Singh et al., 2003), low computational cost (Singh et al., 2002), invariance tolerance of face recognition algorithms based on lines, (Aeberhard & del Vel, 1998) and (Aeberhard & de Vel, 1999).

4.1 Face feature lines

The proposed method is based on the features that we will denominate, face feature lines, FFL. FFL are prominent lines in low resolution face images, and can be extracted using the Hough transform. The Hough transform is a transformation that allows to detecting geometric patterns in images, like lines, circles, and ellipses. The Hough transform, HT, works on a parametric space to define a line by

$$\rho = x \cos \theta + y \sin \theta \tag{5}$$

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. FFL can be extracted from the HT by obtaining the maximum values in the transformation. 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 (Chacon et al., 2006b). The information of these four FFL will be included as components of the feature vector which is defined with detail on further subsections. Figure 8 illustrates how the FFL are obtained.

The feature vector including the FFL is generated as follows:

Step 1. Find the four maximum peak of the HT.

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 $\dfrac{y_{1i}}{1000}$, 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 $\dfrac{y_{2i}}{1000}$, and

include the result to l_{i_2} .

The FFL feature vector can be defined by

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

$$\mathbf{z}_i = \begin{bmatrix} x_{11} + \dfrac{y_{11}}{1000}, x_{21} + \dfrac{y_{21}}{1000} \ldots \\ \\ x_{1i} + \dfrac{y_{1i}}{1000}, x_{2i} + \dfrac{y_{2i}}{1000} \end{bmatrix} \tag{6}$$
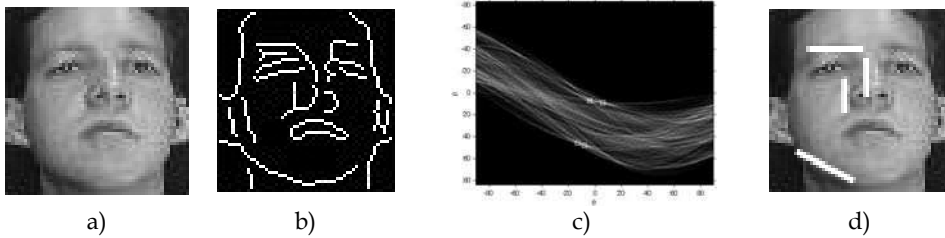

| a) | b) | c) | d) |

Fig. 8. FFL extraction: a) Original image, b) Face edges, c) Accumulator of the HT. d) Original image plus its four FFL.

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

$$\mathbf{X}_{i+xy} = [\mathbf{z}_i \quad \mathbf{i}_{xy}] \tag{7}$$

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.

4.2 Principal component analysis and Karhunen-Loeve transformation

The feature vector is now processed by Principal Component Analysis, PCA, in order to reduce the features dimensionality. This reduction is achieved by the PCA that transforms 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 PCA transformation is accomplished by

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

$$\mathrm{Cov}_{\mathbf{X}} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\mathbf{x}_i - \bar{\mathbf{x}} \right) \left(\mathbf{x}_i - \bar{\mathbf{x}} \right)^T \tag{8}$$

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 $\Phi_1, \Phi_2, ...\Phi_n$ and are associated to $\lambda_1, \lambda_2, ...\lambda_n$.

Step 4. A transformation matrix, $\mathbf{W}_{PCA}$, is created $\mathbf{W}_{PCA} = [\Phi_1, \Phi_2, ...\Phi_n]$.

Step 5. The new vectors $\mathbf{Y}$ are calculated using the following equation

$$\mathbf{Y} = \mathbf{W}_{PCA}^T \mathbf{X} \tag{9}$$

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

The Karhunen-Loeve transformation, KLT, is similar to the PCA (Li & Jain, 2004), however in the KLT the input vectors $\mathbf{X}_i$ are normalized to the interval [0,1] before applying the PCA steps.

4.3 SOM- *k*means face recognition system

The face recognition system is based on a combination of the *k*-means and SOM methods. Its description is presented next.

The system is designed to recognize 10 persons. The design samples considered are the first 8 samples of each individual. This approach generates a training matrix size of 3408x80. The face databases used were the ORL and the YALE.

The classifier design is performed in two steps. First the SOM is trained with the trained samples. The parameters of the SOM using the Kohonen algorithm are; input dimension 3488, map grid size 15X13, lattice type hexagonal, shape sheet, neighborhood Gaussian. Once the SOM has detected the possible classes, Figure 9 a, they are reinforced through the *k*-means algorithm. The *k*-means is applied trying to find 10 clusters, one for each class. Graphical representations of the clusters generated are shown in Figure 9b. Each hexagon in Figure 9b includes the label corresponding to the subject that has been assigned to a specific neuron on the map. The color scale represents the clusters found when the SOM is trained with 8 samples per subject. The U-matrix is a class distribution for graphic representation.
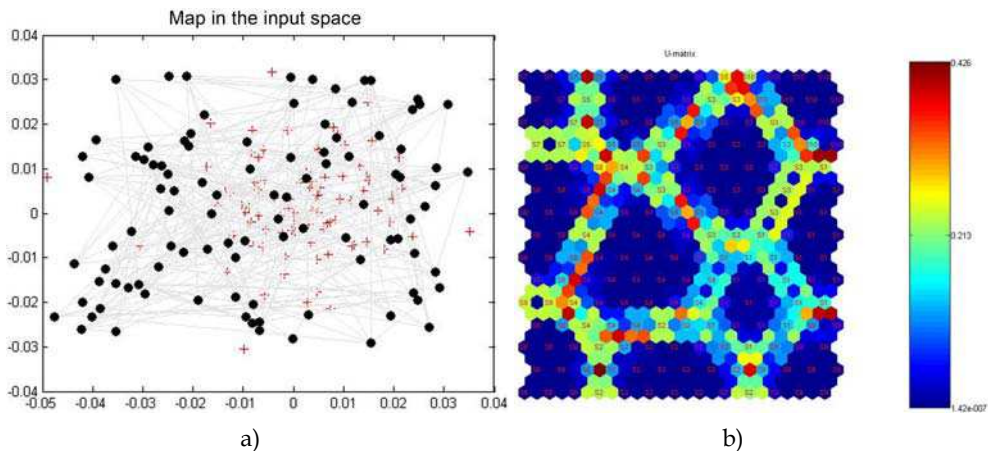

a)   b)

Fig. 9. 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.

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 use of the k-means-clustering algorithm, that reinforces the grouping, may justify this higher recognition rate. 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%.

The general scheme for the SOM-Hough-KLT proposed method is shown in Figure 10.
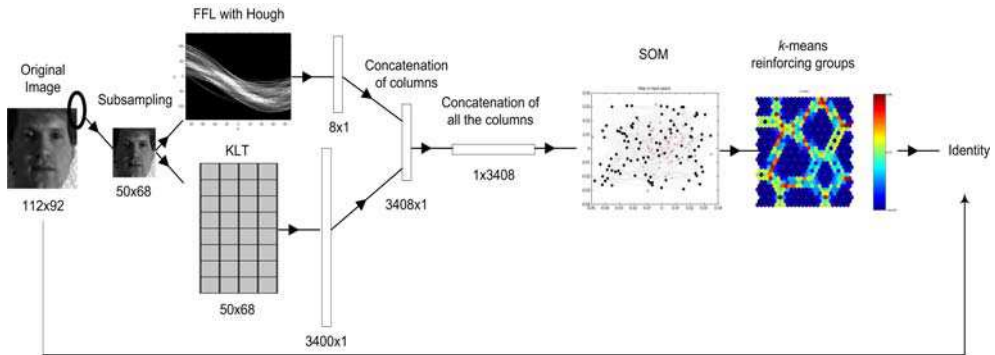
Fig. 10. General scheme for the SOM-Hough-KLT face recognition method.

The propose FRS based on the SOM was compared against a feedforward back propagation scheme for face recognition called FFBP-Hough-KLT. The highest recognition rate on testing reaches 60% on the YALE database, and 92% on the ORL. This result indicates an advantage of unsupervised over supervised systems.

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.

5. Comparison of the proposed method with other classifiers

This section presents a set of experiment results where we compare the performance of several FRS by evaluating the classifiers and the feature vectors. The comparison is considering the average performance of each classifier with respect to the data bases AR, YALE, MIT, and ORL. Table 4 shows the average performance by classifier by data base for the different data bases. ED stands for Euclidean distance, NFL is nearest feature line, FFBP1 and FFBP2 are feedforward neural networks, GG is the fuzzy clustering algorithm Gath-Geva modified by Abonyi – Szeifert (Abonyi et al., 2002), N-D corresponds to a fuzzy neural system using RBF. It can be noted that the SOM has the best performance in two of the four data bases, and it is not far from the best performance of the best FRS in the other two cases. Besides the SOM has the higher performance reached of all FRS, with 92.86%. The highest performance is in the ORL data base as expected because it has less variation with respect to PIE. Contrary to the AR and YALE data bases that have more PIE variations.

With respect to the type of classifier system, the systems based on Artificial Neural Networks and Fuzzy Logic resulted to be the most consistent on their performance over a set of 14 recognition experiments taking different sets of faces as shown in Figure 11.The experiment number 8 had the lowest performance because some of the worst face images were included on that testing set. We can also observe that the SOM approach was the best FRS among the fuzzy and ANN classifiers.

Data base	FRS						
	ED	NFL	FFBP 1	FFBP 2	SOM	GG	N-D
AR	85.49	87.00	83.25	85.15	88.59	78.82	75.61
YALE	89.79	90.73	84.79	86.76	89.76	80.17	75.61
MIT	90.52	91.29	86.48	88.11	91.11	81.66	79.24
ORL	84.49	85.38	88.78	90.05	92.86	83.62	83.27

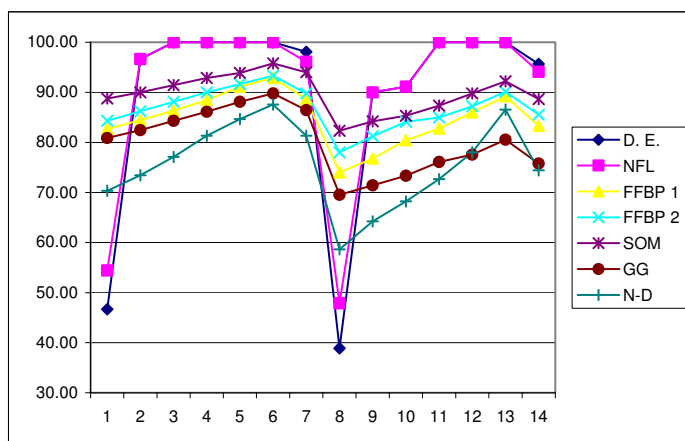Table 4. Classifier performance by data base.

Fig. 11. Performance by type of classifier in the 14 experiments.

Another important finding in these experiments is that the Hough-KLT feature yielded the best performance compared with the other features as shown in Table 5 over the different data bases. This result may reinforce the use of the face feature line feature. In this table DDWT stands for Wavelet features, and dB is the wavelet level used.

6. Results, conclusion and future work

The chapter presented an analysis of 30 works on FRS. The works were analyzed for tolerance to image variations, feature extraction methods and classifier system used. Results indicate that the most considered variation in the works is related to face expression, one of the most used method for feature extraction turned to be wavelet based methods, and the classifiers with more use are based on Euclidean distance. In order to compare the performance of the different works a new performance index was proposed. The best performance for a FRS assuming PIE tolerance reached 91.96%.

Feature	Data base			
	AR	YALE	MIT	ORL
DDWT-KLT db1	82.12	85.18	87.42	86.56
DDWT-KLT db2	82.82	85.13	87.36	86.98
DDWT-KLT db4	83.42	86.24	87.74	86.66
KLT	82.09	83.95	85.52	86.01
Gabor-KLT	81.81	84.18	85.10	86.02
Hough-KLT	86.69	88.57	89.32	89.43
Eigenfaces	80.51	82.52	84.59	85.12

Table 5. Performance by features.

The chapter also covered an alternative point of view for FRS based on human facial perception theories. This part of the chapter, presented some neurophysiologic theories that may be useful to design more robust FRS. In fact, one of these theories, newborn visual perception, is proposed to be incorporated in a novel face recognition approach that is described in the chapter. The newborn visual perception idea led us to consider low resolution features extracted with the Hough transform, FFL, to design a FRS.

The FRS designed is based on a SOM- $k$means classifier. The performance achieved during testing were, 90% for the ORL, 70% for the YALE database. As expected, the performance has lower rates on the YALE database because of the variations in lighting conditions of the database. However the performance is comparable with current face recognition systems based on PCA which achieves 77%.

In a final experiment, the proposed method was compared against 6 other methods using the AR, YALE, MIT, and ORL data based. The proposed method turned to achieve the best performance in two of the test, with 88.59% and 92.86%, and it was the second best in the other two, 89.76% and 91.11%. Another important result in this experiment is that with respect to the type of classifier system, the systems based on Artificial Neural Networks and Fuzzy Logic resulted to be the most consistent on their performance over a set of 14 recognition experiments. Besides, the SOM approach was the best FRS among the fuzzy and ANN classifiers.

Still another important finding in these experiments is that the Hough-KLT feature, that incorporates the FFL, yielded the best performance compared with the other features.

Based on the previous results, we can conclude that incorporation of neurophysiologic theories into the design of FRS is a good alternative towards the design of more robust systems. We also may conclude that FRS based on ANN, specially with unsupervised systems, represent a good alternative according to the results of the experiments reported in this chapter.

As future work, we propose to achieve a more complete research towards the integration of the results presented in (Sinha et al., 2006) into FRS design in order to evaluate the real impact of these theories in real world applications.

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8. References

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Notwithstanding the tremendous effort to solve the face recognition problem, it is not possible yet to design a face recognition system with a potential close to human performance. New computer vision and pattern recognition approaches need to be investigated. Even new knowledge and perspectives from different fields like, psychology and neuroscience must be incorporated into the current field of face recognition to design a robust face recognition system. Indeed, many more efforts are required to end up with a human like face recognition system. This book tries to make an effort to reduce the gap between the previous face recognition research state and the future state.

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