Mobile Robot for Face Recognition: A Collaborative Environment

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ABSTRACT

Nowadays human beings need to perform dangerous tasks involving the possibility of physical injury. This creates a demand of novel collaborative technologies between human and machines. In this paper we present a collaborative scheme aimed to support a mobile face recognition system for surveillance applications. Such face recognition system is based on facial feature lines and the Abonyi's and Szeifert's fuzzy classification scheme. A mobile platform which uses the latest technologies in mobile robotics is introduced. The implementation shows facial recognition rates up to 95% with the ORL facial database, and successful assessment for remote scene monitoring.

KEYWORDS: Mobile robotics, face recognition, human robot interaction, fuzzy clustering.

1. INTRODUCTION

In the last decade, security systems have been reinforced since new advances in technology became available. Biometric systems are an example of security systems in which new advances in machine learning and soft computing are taking the industry to evolve its recognition techniques into better ones. Biometric systems based on face recognition have high recognition rates when face images are acquired under controlled conditions. However, robust face recognition systems need to be capable of operate under uncontrolled conditions of pose, illumination, and facial expression (PIE) [1]-[8]. Two of the most important face recognition methods currently used are the eigenface and Fisherface methods. The eigenface method, also known as principal component analysis (PCA), is an accepted method for vector feature representation in face recognition [9]. PCA is a popular method in pattern recognition and is quite often referred to as Karhunen–Loève transformation (KLT). The PCA approach exhibits optimality when it is applied to reduce the dimensionality of a feature vector [9]. Face recognition methods have strong foundations with almost 30 years of research in the field; however, face recognition under PIE variations have not achieved 100% of recognition rates. Therefore, new schemes need to be explored. Moreover, robotics and biometric technologies are becoming a new research field for environments where human beings need to perform face recognition but they have the risk of being injured, i.e. a hostage situation. This is where the Human-Robot Interaction (HRI) takes place. In such case, a person will be able to explore environments in collaboration with a mobile robotic system. That is, the robot will provide with images of the scene, and the human will interact with the robot by giving it directions through a computer.

From our previous work in face recognition [10-13] and in robotics [14-15], we propose an interdisciplinary project between the areas of mechanical, software, and electrical engineering. The proposed collaborative architecture involves robotics and pattern recognition fields into a mobile face recognition robotic system as shown in Figure 1. We propose the KLT (PCA) approach to map an original feature vector to a new feature space. Then we improve the traditional face recognition methods, trough the incorporation of fuzzy logic theory, based on facial features [10-11]. The incorporation of such features is based on studies related to face recognition on newborns [3]. The feature vector used to achieve face recognition is a combination of the facial feature lines and eigenvectors computed through the KLT.

Two novel face recognition-classification methods are presented in this paper. One method is based on the

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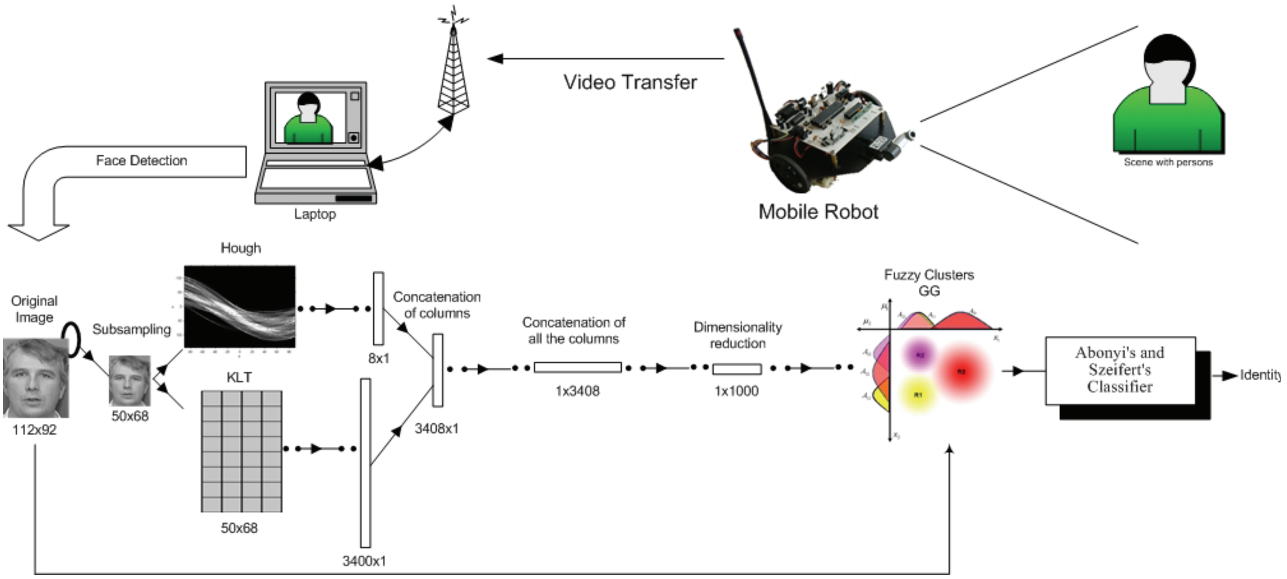

Figure 1. Proposed Scheme for a Mobile Face Recognition System in Non-Cooperative Environments.

Euclidean distances of the feature vector in the KLT hyperplane, and other method based on fuzzy clustering and the Abonyi's and Szeifert's classifier. The performance of the face recognition system is evaluated by comparing the two classification methods, while the performance of the mobile robot is measured through speed control analysis. We also discuss the collaboration between the mobile face recognition and the human being. In Section 2 is presented the mobile robot design. The features extracted from facial images are explained in Section 3, while in Section 4 is presented the classification algorithm based on fuzzy theory. In Section 5 is explained the collaborative scheme, and finally, in Section 6 conclusions are drawn.

2. MOBILE ROBOT HARDWARE DESIGN

In our robot we propose the usage of a "differential" configuration because of its simplicity. Such configuration involves two motor wheels and one or more free wheels, which provides the robot with motion stability. Using such configuration, every turn is achieved through independent motor speed variations. In Figure 2 a) is described graphically the differential configuration. In Figure 2 b) is shown the proposed hexagonal shaped chassis design, which was selected for simplicity in robot prototyping and also due to the space constraint produced by the batteries, the printed circuit board (PCB) and the motors.

Robot's motion is provided by the direct current (DC) motors. In this research, the best choice was the GM2 model since the operation voltage is low, extending the battery duration due to the low power consumption. This motor also provides a very good torque-velocity response.

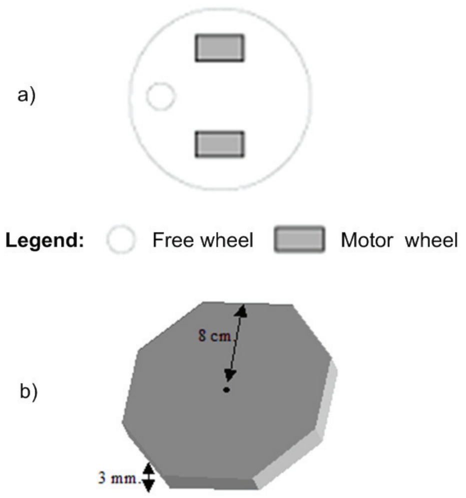

Figure 2. a) Differential Configuration; b) Dimensions.

The control of the robot's motion is achieved using "motor encoders", sensing each motor. Then this information is sent to a microprocessor (microcontroller). The microcontroller creates a closed loop by sending feedback (voltage) indicating the motor to stop, or to continue, as explained in Figure 3. Such feedback is performed through a driver (L298N), which was selected because of its performance, fast response, low voltage consumption, and compatibility with the GM2 motors.

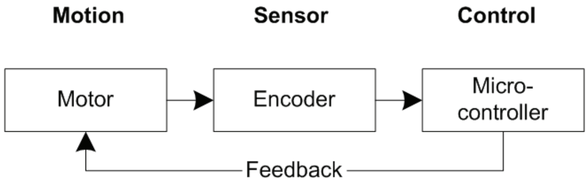

Figure 3. Motion Control Architecture.

The proposed mobile robot has the ability to communicate with a PC through serial communication using the integrated circuit MAX232. All the information bits are transmitted via radio frequency (RF). Such RF transmission is performed with the TWS-434A and received with the RWS-434A modules over a frequency of 433.9 MHz. We used the microcontroller PIC 18F4520 to store and execute the software for motor control, which is introduced in the following section.

2.1. Independent Control

The control of a motor spin is a whole research area in which many different techniques can be utilized to give the results needed. Control theory is not the purpose of this paper. However, we will emphasize the results when the "Proportional" control theory is applied to this particular application.

The Proportional control is a method in which the output (in this case velocity) of a motor p is measured and compared with an error ε, by computing its difference. If there is a positive difference, it means that more voltage is needed in the motor, but if the difference is negative, then the voltage going to the motor must decreased proportional to the error. We performed several experiments with different control methods. Such methods were the traditional Integral, Derivative and the combination of the three. The best results were obtained with the proportional control method. The effects of implementing a control methodology versus not having one are shown in Figure 4. The desired spin speed can be efficiently achieved way using Proportional control.

The capture and transmission of images is an independent module in the robot. Images are acquired and transmitted wirelessly to a PC for its processing and analysis. Such analysis is introduced in the following section.

3. FACIAL FEATURE EXTRACTION

The different parts of the proposed feature extraction method are described in this section. The method proposed here represents a novel approach which incorporating recent ideas from the visual perception point of view related to face recognition. From visual perception studies, it is known that some spatial face features like, mouth to nose distance, geometric shape between the mouth and the eyes, and face feature lines, are distinguishing characteristics. The features selected and incorporated in the proposed method correspond to face feature lines, FFL. Face features lines are prominent lines and can be extracted with the Hough transform from low resolution image faces, and are important features documented in newborn face recognition studies [3]. Studies with newborns have shown that babies perceive a totally-fuzzy world in terms of human vision. Their only tool to recognize faces are facial lines and circles [2-3]. This suggests that the use of lines for face recognition is a theory also supported by the psychology and neurology regarding face perception.

3.1. Hough Transform for Face Feature Lines

Hough transform is a method useful 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

$$\rho = x\cos\theta + y\sin\theta \tag{1}$$

where x and y represent the coordinate of a pixel in the image, ρ is the distance of the line to the origin, and θ is the angle of the line with respect the horizontal axis. In general, the HT algorithm requires a binary image as input, which represents the edges of the image [16]. In this work the edge detection algorithm used was the Canny operator. Once the image edges are obtained, the HT is computed and the result represent all the line patterns in the space (ρ, θ). Given this result we can extract the FFL by obtaining the maximum points from the HT through ρ, and θ.

In our previous work [10-13] we showed that four face feature lines improve the performance of a face recognition system. This assumption is based on the experiments related to the newborns vision system. The information of these four FFL will be included as components of the feature vector which is defined on further subsections.

In summary, the result of apply the HT to a face for locating the four FFL is illustrated in Figure 5. For the generation of the first part of the features vector from the coordinates of its four FFL, the following method was designed:

Step 1. Get the four maximum peak values.
Step 2. Get the four characteristic lines coordinates.
Step 3. Encode the coordinates information by taking the value of x_{1i} and add it to $y_{1i}/1000$, and include the result to l_{i_1}.
Step 4. Take the value of x_{2i} and add it to $y_{2i}/1000$, and include the result to l_{i_2}.

The feature vector can be defined as follows

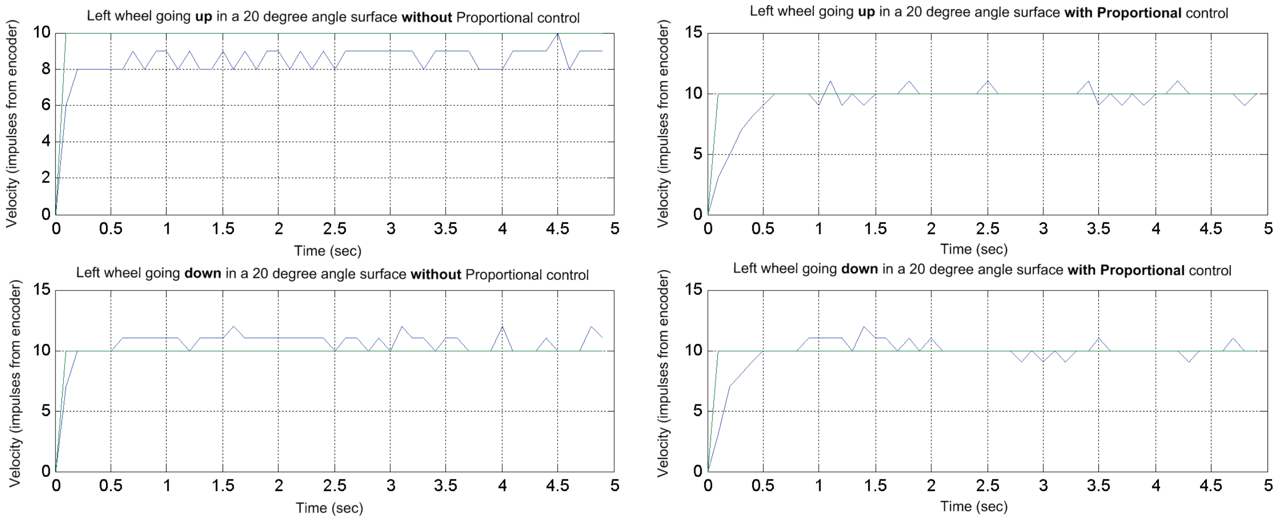

Figure 4. For a Desired Velocity of 10: In (Left) Without Control; in (Right) Using Proportional Control.

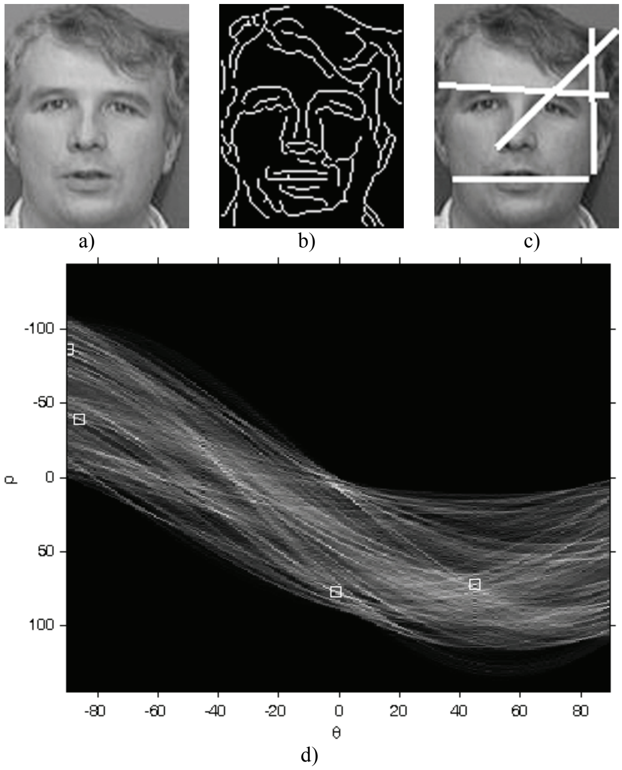

Figure 5. a) Original; b) Edges; c) FFL+a); d) HT.

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

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

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

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

The vector $\mathbf{z}_i$ is linked to the information of the original image to complement facial information before the KLT.

3.2. Principal Component Analysis

The objective of PCA is to transform the data $\mathbf{X}$ into a new space $\mathbf{Y}$, where the data is decorrelated. The final objective in our proposed scheme is to reduce the dimensionality of the feature vector using PCA [16]. The new vectors $\mathbf{Y}$ are calculated using the following equation

$$\mathbf{Y} = \mathbf{W}_{PCA}^{T}\mathbf{X} \tag{4}$$

where T denotes the transpose of $\mathbf{W}_{PCA}$, and $\mathbf{X}$ denotes the matrix containing all the feature vectors. KLT is similar to the PCA [13], however in the KLT the each dimension of the input vectors $\mathbf{x}_i$ is normalized to the interval [0,1] before applying the PCA steps.

3.3. Hough-KLT Implementation and Performance

The vector $\mathbf{x}_{i+xy}$ as described before, is composed by 8 coefficients $\mathbf{z}_i$, and by the original image $\mathbf{i}_{xy}$. All feature vectors are transformed with the KLT method. Face recognition can be achieved with the transformation matrix, $\mathbf{W}_{KLT}$, following the next steps.

Step 1. For an unknown facial image generate its $\mathbf{i}_{xy}$ representation.

Step 2. Compute the 8 $\mathbf{z}_i$ elements with (2).

Step 3. Generate $\mathbf{x}_{i+xy}$ with (3).

Step 4. Compute $\hat{\mathbf{x}}_{i+xy} = \mathbf{W}_{KLT}^{T}\mathbf{x}_{i+xy}$ with (4).

Step 5. Assign the facial image I_{face} to the class C_j If

$$D(\hat{\mathbf{x}}_{i+xy},\hat{\mathbf{x}}_j)=\left\|\hat{\mathbf{x}}_{i+xy}-\hat{\mathbf{x}}_j\right\|<\left\|\hat{\mathbf{x}}_{i+xy}-\hat{\mathbf{x}}_k\right\| \quad \text{for all } \mathrm{j},k \ \ \mathrm{j}\neq k \tag{5}$$

where $\hat{\mathbf{x}}_i$ represents the transformed feature vectors of the training faces.

This classifier along with the 10-fold cross validation method was tested on the ORL database. The classifier has a performance of 91% of correct classification keeping the largest 25 eigenvectors. If the FFL's are included in the feature vector the performance increases to 95%. Also this classifier along with the 10-fold cross validation method was tested on the Yale database. The classifier had a performance of 88% of correct classification using 25 eigenvectors. If the FFL are included in the feature vector the performance increases to 90%. These results are shown in Table 1.

The "Olivetti Research Laboratory" (ORL) face database has slight variations on pose, illumination, facial expression (eyes open/closed, smiling/not-smiling) and facial details (glasses/no-glasses) [13][14]. ORL has 40 different subjects. In Figure 6 a) is shown an example 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 [17]. In Figure 6 b) are shown samples of two different subjects under the conditions described above.

4. FUZZY CLASSIFICATION

Commonly the membership functions of a fuzzy system are designed according to the experience of an expert who knows the behavior of a process. Fuzzy clustering is a technique widely used to create the membership functions of a fuzzy system [18][19]. Applying clustering methods we can obtain fuzzy sets and utilize them to model the antecedents of the rules a fuzzy system. This is obtained by the projection of the fuzzy sets, as shown in Figure 7.

4.1. Abony and Szeifert's Classifier

The classifier proposed by Abonyi and Szeifert [20] defines the consequent of the fuzzy rule as the probabilities of the given rule to represent the $c_1,\ldots,c_c$ classes:

Table 1. Classifier Performances on ORL and YALE

	ORL		YALE	
CLASSIFIER	No FFL	FFL	No FFL	FFL
EUCLIDEAN	91%	95%	88	90

a)

b)

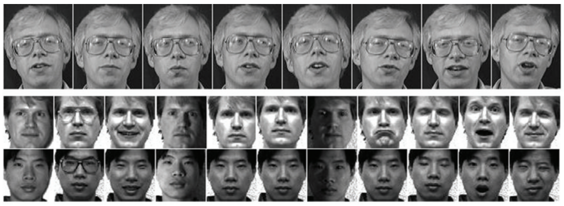

Figure 6. Sample Faces from a) ORL and b) YALE.

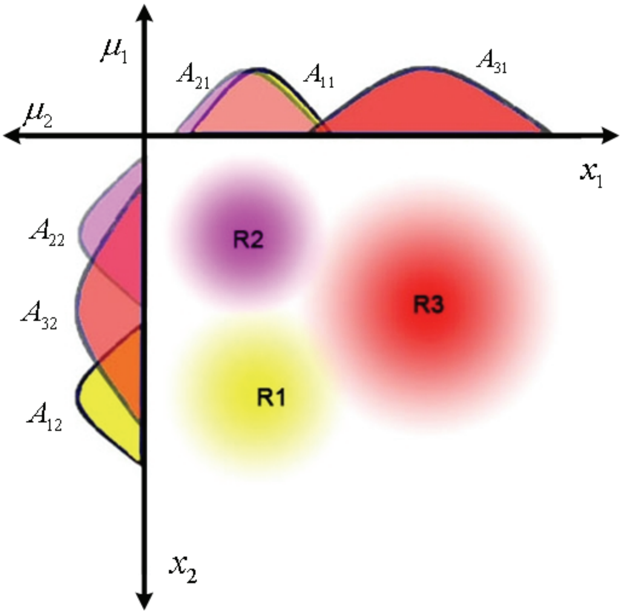

Figure 7. Three Fuzzy Sets and Cluster Projections.

$$\begin{aligned} r_i:\ & \textbf{if } x_1 \ is\ A_{i,1}(\hat{\mathbf{x}}_{1,k}) \ \ \textbf{and} \ldots x_n\ is\ A_{i,n}(\hat{\mathbf{x}}_{n,k}) \\ & \textbf{then } \hat{y}=c_i \ with\ p(c_1 \mid r_i) \ \ [w_i] \end{aligned} \tag{6}$$

Similarly to Takagi-Sugeno fuzzy models, the rules of the fuzzy model are aggregated with the normalized fuzzy mean formula. The label of the class that has the highest activation determines the output of the classifier:

$$\hat{y}_k = \arg\max_{1\le i\le c} \frac{\sum_{l=1}^{R}\beta_l(x_k)P(c_i \mid r_l)}{\sum_{i=1}^{R}\beta_l(\hat{\mathbf{x}}_k)} \tag{7}$$

where

$$\beta_i(\hat{\mathbf{x}}_k)=w_i A_i(\hat{\mathbf{x}}_k)=w_i e^{-\frac{1}{2}\left(\hat{\mathbf{x}}_k-\mathbf{v}_i\right)^T(\mathbf{F}_i)^{-1}\left(\hat{\mathbf{x}}_k-\mathbf{v}_i\right)} \tag{8}$$

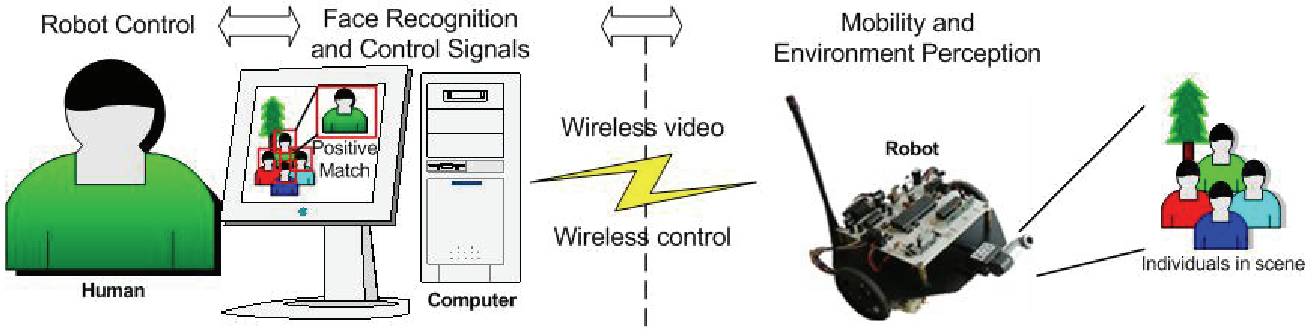

Figure 8. Interaction between Human, the Computer, and the Mobile Robot. Proposed Collaboration.

$$w_i = \frac{P(r_i)}{\left|2\pi \mathbf{F}_i\right|^{n/2}} \tag{9}$$

where $\mathbf{v}_i = \left[v_{1,i},\ldots,v_{n,i}\right]^T$ denotes the center of Gaussian functions, and $\mathbf{F}_i$ is equal to the diagonal of the matrix that contains the variances $\sigma^2_{i,j}$. Equation (8) defines how the membership functions $A_i(\hat{\mathbf{x}}_k)$ are created. These functions are generated by projecting the data of the created clusters, its centroids v_i, with the diagonal of the matrix containing the variance of the cluster, $\sigma^2_{j,i}$. The centroid of the *i*-th cluster will be the same as the center of the *i*-th Gaussian function; therefore, the number of clusters is the same as the number of functions.

In this work we utilize a cluster quality validation function, *S*, proposed by Xie and Beni [11] that is designed to measure the overall average compactness and separation of the fuzzy partition.

4.2 Abonyi's and Szeifert's GG Algorithm

The fuzzy classifier can be summarized with the following steps.

Step 1. Given a set of data $\hat{\mathbf{x}}_k$ where $\hat{\mathbf{x}}_k = \left[\mathbf{x}_k^T \; \mathbf{y}_k\right]$, $\mathbf{x}_k$ denotes the vector to be classified, and $\mathbf{y}_k$ denotes the class corresponding to $\mathbf{x}_k$. Use the GG clustering algorithm [18], in order to obtain $\mathbf{U} = \left[\mu_{i,k}\right]_{cxN}$.

Step 2. Once we have the fuzzy matrix **U** we can start the design of the fuzzy model, similar to the Takagi-Sugeno, where the rules of the fuzzy model are added using the formula for a normalized fuzzy mean. First we calculate the activation grade of the rules β with (6). Then we compute the output of the classifier with (7). The membership functions are evaluated with (8) and the rule weight is computed with (9).

4.4 Testing the Abonyi's and Szeifert's GG Algorithm

The proposed method combining FFL, GG clustering algorithm and Abonyi-Szeifert's classifier was tested with the ORL database. In the design stage, 8 out of 10 faces of 40 persons were used in the GG clustering algorithm. During the verification the other two faces of each individual was submitted to the face recognition system. The system had a performance of 90% of correct classification. When the FFL are removed from the feature vector the performance drops to 88.5%. Also the proposed method was tested with the Yale database. In the design stage, 8 out of 10 faces of 10 persons were used. During the verification the other two faces of each individual was submitted to the face recognition system. The system had a performance of 89% of correct classification. When the FFL are removed from the feature vector the performance drops to 85%.

5. CONCLUSIONS

We have proposed a collaborative environment (Figure 8) for a mobile face recognition robotic system (Figure 1). We discussed the unique design of a mobile robot, as well as the control methodology for motion speed. The implementation of Proportional control demonstrated very good results. For the face recognition methodology we proposed the KLT (PCA) to map an original feature vector to a new feature space. Using fuzzy logic theory along with the incorporation features based on studies related to face recognition on newborns we improved traditional face recognition methods.

Two face recognition classification methods were described. One is based on the Euclidean distance of the feature vector in the KLT space, and other based on fuzzy clustering and classification. The Euclidean distance classifier obtained a correct classification performance of 91% keeping the 25 largest eigenvectors and 95% if the face feature lines are included. Fuzzy clustering and classification systems, illustrated in Figure 1, reached 88.5% of correct classification using a feature vector keeping its 25 largest eigenvectors and 90% of correct classification if the face feature lines are included in the feature vector. Table 2 summarizes the results, and clearly shows that FFL improve the performance. The results over ORL and YALE databases also show that our methods for face recognition are robust against PIE variations with no additional pre-processing algorithms.

In a general sense, this paper presents a unique collaborative scheme between the human, the computer and the robot, in order to perform surveillance tasks. The implementation of such scheme demonstrated good results in controlling the robot, transmitting images and performing face recognition tasks.

Table 2. Classifiers Performance on Facial Databases

CLASSIFIER	ORL No FFL	ORL FFL	YALE No FFL	YALE FFL
EUCLIDEAN	91%	95%	88%	90%
FUZZY CLUSTERING	88.5%	90%	86%	90%

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