2. THE PROPOSED APPROACH

The proposed approach for facial face recognition consists of three main steps: detection, localization and recognition. To illustrate well we proceeded as follows:

First the face is detected by the HSV color segmentation of the skin. Then, the features are located based on the variation of gray level along the axis of the feature, and also applying the geometrical model for the limit, as result in seeking to frame the face and resize an image size below to apply the Fourier transform of Gabor filters. Finally, the method of regularized linear discriminate analysis is applied for recognition.

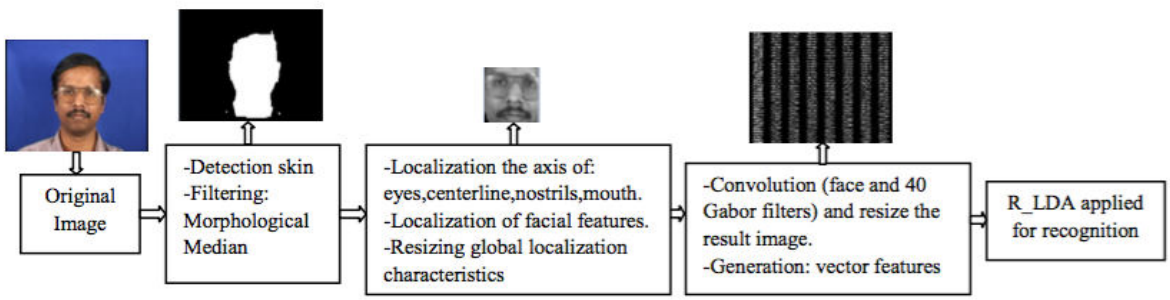

Fig 1: Architecture description of the proposed approach.

2.1 Primary Methods of detection and localization

We chose HSV color space for detecting pixels having the color of the skin and for locating properties that are used by local variation in gray level along the axis of the feature seen face and the geometrical model.

2.1.1 Methods of detection

Face detection task is complex because it is influenced by several factors: complex environments, changes in lighting, pose and expression changes.

We chose the face detection based on skin color by using the HSV space because it offers good performance, which is to classify each pixel of the image into two types: pixel (skin) or (not skin), then it has improved the image obtained by mathematical morphology and median filter.

2.1.2 Methods of localization

There are many methods for facial feature extraction based on gradient information, they are robust to lighting changes, and others are using color information. There only work with color images and illumination changes, which can affect the results.

To make an initial localization of characteristic objects in the area detected by the previous step we propose a new method based on the aspect of gray level along the main characteristics of the eyes and nose down, first we have determined the axis of the eyes, middle, lower nose and mouth.

2.1.2.1 Localization of the axis of eyes

The horizontal axis containing eyes is the line that has the maximum change in the level of gray. This corresponds to several transitions: skin to the eye, white of the eye to the iris, the iris to the pupil and the same thing on the other side.

We calculate the gradient of the entire image to determine the axis of the eye, in our method we calculate the convolution of the horizontal image twice by (-1, 0, 1).

□◆ Algorithm1:

1. Convolution of the image I gray level by [-1,0,1] twice:

$$C=\left(I \;\; [\;\; 1\; 0\; 1]\right) \;\; [\;\; 1\; 0\; 1] \qquad ....(1)$$

2. Transform the C in absolute.

$$G = |C| \qquad ....(2)$$

3. Horizontal projection of G:

$$H(y) = \sum_{x=0}^{n-1} G(x,y)$$

Such as n: image width. ....(3)

4. Find the maximum horizontal projection of G.

Fig. 2 shows the image after step 2 with its horizontal projection, where we note that the maximum of the curve corresponds to the axis of the eyes.

***Fig 2**: Localization of the axis of the eyes by convolution of the image.*

2.1.2.2 Localization of the centerline

The center line intersects the face vertically into two symmetrical parts, we seek the position of the gray level higher on the axis of the eyes (Fig 2), and the maximum of the curve corresponds to the centerline because it corresponds to the region that contains the maximum amount of skin. However, we are interested in the change of gray level on the axis of the eye such that the segments in both left and right sides respectively of the left eye and right have a change of gray level zero (Fig 3) but segment that corresponds to several transitions (the white eye of the eye to the iris, iris to the pupil and the same thing on the other side) has a significant change in gray level.

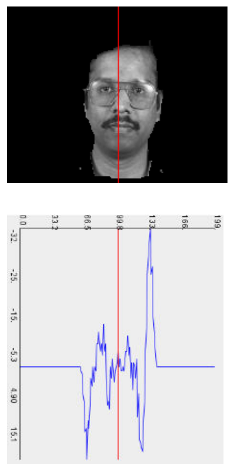

Fig 3: *Localization of the vertical centerline.*

Note that the middle of segment in which there is a big change, is the central axis.

2.1.2.3 Localization the axis of the nostrils

The axis of the nostrils is the line that contains less than pixel of the skin located below the axis of the Eye. For precise localization, we took the area around the nostrils below the axis of the eyes and around the centerline with a width of 14 pixels (Fig 4).

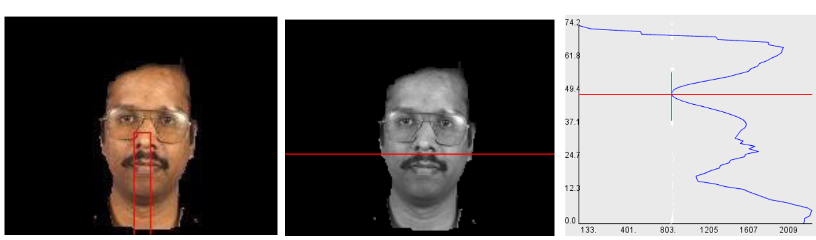

Fig 4: *Localization the axis of the nostrils.*

2.1.2.4 Localization of the axis of the mouths

Based on the same approach to subsection (2.1.2.1 Localization of the axis of eyes) the axis of the mouth is the first maximum located below the axis of the nostrils (Fig 5).

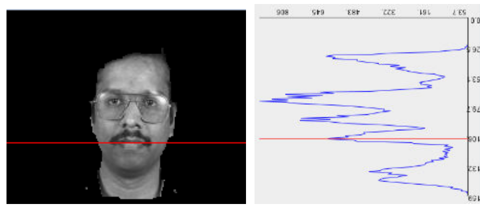

Fig 5: *Localization the axis of the mouth.*

2.1.2.5 Geometric model

After the axis of the eyes and mouth are located, we apply the geometric model of face to extract facial features given in:

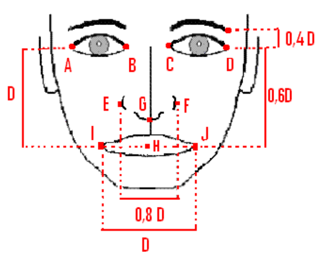

Fig 6: *The geometrical model of face.*

- The vertical distance between the eyes and center of the mouth is D.
- The vertical distance between the eyes and center of the nostrils is 0.6D.
- The width of the mouth is D.
- The width of the nose is 0.8D.
- The vertical distance between the eyes and eyebrows is 0.4D.

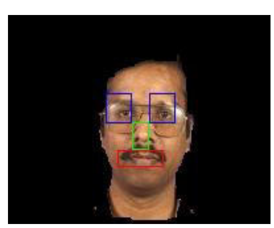

Fig 7: *Localization of characteristics.*

2.2 Face Recognition Facial

Images of faces detected by our system could be used as input for a face recognition system facial.

2.2.1 The representation of the face with Fourier- Gabor filters

Among the new techniques used in the literature for feature extraction, we use the Gabor transform. We introduced this technique because it has proven its performance to improve face recognition using the combination of Fourier and Gabor filter.

In our approach we use Gabor wavelets and Fourier for feature selection as these present desirable characteristics of spatial locality and orientation selectivity. Several works have also shown that the Gabor wavelet representation of face images is robust against variations due to illumination and facial expression changes.

2.2.1.1 Fourier Transformed Image

Fourier Transformed image is the image I in the frequency domain as in this field every point represents a particular frequency contained in the image space of square image of size N × N.

$$Fourier(m,n,I)=\frac{1}{N^2}\sum_{a=0}^{N-1}\sum_{b=0}^{N-1} I(a,b)\ e^{-i2\pi\left(\frac{ma+nb}{N}\right)} \quad ....(4)$$

2.2.1.2 Gabor Filters

Gabor is a function that satisfies certain mathematical requirements and it is used in the presentation of data, however, it represents data at different scales and orientations. Gabor filters have been applied in many applications such as texture segmentation, image representation, edge detection and face recognition. Extraction information is based on the use of a bank of Gabor filters, 8 orientations and 5 resolutions.

$$Gabor(x,y,\mu,v)=\theta(x,y,\mu,v)\left(\alpha-\beta\right)$$

Where:

$$\theta(x,y,\mu,v)=\frac{\left\|k_{\mu v}\right\|^2}{\sigma^2}\exp\left(\frac{-\left\|k_{\mu v}\right\|^2\left(x^2+y^2\right)}{2\sigma^2}\right)$$

$$\alpha=\exp\left(ik_{\mu v}*(x,y)\right),\ \beta=\exp\left(\frac{-\sigma^2}{2}\right) \quad ....(5)$$

Where (x,y) represents a 2-dimensional input point. The parameters μ and ν define the orientation and scale of the Gabor kernel. ||.|| indicates the norm operator, and σ refers to the standard deviation of the Gaussian window in the kernel.

The wave vector K μυ is defined as:

$$k_{\mu\nu} = k_{\nu} \exp^{i\varphi_{\mu}} \qquad \text{....(6)}$$

$$\text{Where: } k_{\nu} = \frac{k \max}{f^{\nu}}, \quad \varphi_{\mu} = \frac{\pi\mu}{8}$$

If 8 different orientations are chosen. K_{max} is the maximum frequency, and f^{υ} is the spatial frequency between kernels in the frequency domain. In our configuration, 5 different scales and 8 orientations of Gabor wavelets are used, e.g. ν € {0, ... , 4} and μ€ {0, ..., 7}. Gabor wavelets are chosen with the parameters:

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$$k \max = \pi/2 \qquad \text{....(7)}$$

$$f = \sqrt{2} \qquad \text{....(8)}$$

$$\sigma = \pi \qquad \text{....(9)}$$

The collection of all 40 Gabor kernels is called a filter bank. An example can be found in Fig 9.

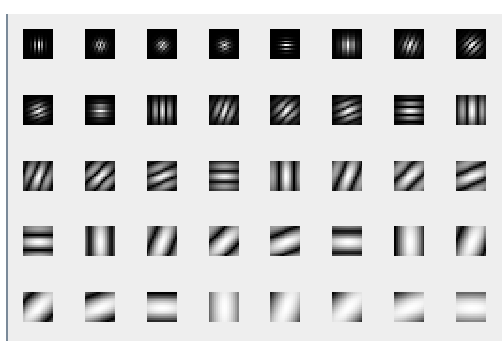


***Fig 9**: Gabor filters of size 16 × 16 by 8 orientations and 5 Resolutions (real part).*

The Fourier Gabor wavelet representation of an image is the convolution of the Fourier image with the Fourier filter bank.

$$O_{\mu\nu}(x,y) = F\left(I(x,y)\right) * F\left(\psi_{\mu\nu}(x,y)\right) \quad ....(10)$$

and called Fourier Gabor feature. As the response $O_{\mu,\nu}(x,y)$ to each Fourier Gabor kernel is a complex function with a real part : Real{ $O_{\mu,\nu}(x,y)$} and an imaginary part : Imag{ $O_{\mu,\nu}(x,y)$},we use its real Real{ $O_{\mu,\nu}(x,y)$} to represent the Fourier Gabor features. The complete set of Gabor wavelet representations of the image I(x,y) is:

$$G\ (I) = \{O\mu\nu\ (x,y) : \mu \quad \{0,..,7\}, \nu \quad \{0,..,4\}\} \quad ....(11)$$

The resulting features for each orientation, scale are referred to as Fourier Gabor feature vector.The following algorithm shows the steps of respectful representation of the face with Fourier- Gabor filters.

- Algorithm2:

1. Prepare 5 × 8 matrix Gabor each of size 16 × 16 as shown (Fig 9).

2. Apply the Fourier transform to each matrix Gabor.

3. Apply Fourier to each image in the training set of size 32×32 (obtained in section 2.1.2.6).

4. Convolution of the Fourier transform of the image size 32×32 by each image of the Fourier transformed Gabor size 16 × 16 (8 orientations and 5 scales) .

5. Construct the image Fourier_Gabor_IMG (5×8×32×32) from the sub images (32×32 obtained in step 4) (Fig 10).

6. Resize the image Fourier_Gabor_IMG to 100× 100.

***Fig 10**: Fourier_Gabor_IMG (5×8×32×32) Results Convolution of Fourier transformed image (32 × 32) for the Fourier transformed of each Gabor filter 16× 16.*

The use of Gabor filters is very expensive in computing time, due to the convolution of the whole image with filter size 16 × 16. For this reason, we limit the use of the image size of 32 × 32 convolved with 40 Gabor filters: 8 orientations and 5 scales resizing the vector of features that has the size of (5×8×32×32=40960) to 100× 100.

After the generation of vector features by Fourier and Gabor filter, the method of regularized linear discriminate analysis (R_LDA) is applied for recognition.

2.3 Regularized Linear Discriminate Analysis (R_LDA)

In introduced the method of regularized linear discriminate analysis (R_LDA), for purposes for recognition, which discriminate group, the feature vectors (obtained in Algorithm 2) of the same class and separates the feature vectors of different classes. The feature vectors are projected from N^2-dimensional space to C dimensional space (where C is the number of classes of the feature vectors and N=100).

The R_LDA is divided into two phases; one for the calculation of training feature vectors system and the other is to recognize a feature vectors tested in relation to registered models. We describe the R_LDA algorithm as follows:

- Algorithm3:
- Training:

1- For each class I = 1, ... , C, calculate the mean vector as μ_c in (12). And calculate the mean vector as μ in (13).

$$\mu_c = \frac{1}{N_c} \sum_{i \in c} x_i \qquad \text{....(12)}$$

$$\mu = \frac{1}{n} \sum_i x_i = \frac{1}{n} \sum_c N_c \mu_c \qquad \text{....(13)}$$

n: the number of training face

2- The within-class scatter matrix Sw and the between-class scatter matrix S_B are defined as:

$$S_w = \sum_{c} \sum_{i \in c} (x_i - \mu_c)(x_i - \mu_c)^T \qquad (14)$$

$$S_B = \sum_{i=1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T = \sum_{i=1}^{c} \phi_{b,i} \phi_{b,i}^T = \Phi_b \Phi_b^T \qquad (15)$$

3- Find the m eigenvectors of $\Phi^T \Phi$ with non-zero eigenvalues, and denote them as

$E_m = [e_1, \cdot \, . \, , e_m]$, where m = c-1.

4- Calculate the first m most significant eigenvectors (U_m) of S_B and their corresponding eigen values (Λb) by:

$Um = \Phi_b E_m$ and $\Lambda b = U^T{}_m S_B U_m$

5- Let $H = U_m \Lambda b^{-1/2}$. Find eigenvectors of $H^T S_w H$, $P = [p_1,.., p_m]$ sorted in increasing eigen value order.

6- Choose the first M ($\leq$ m) eigenvectors in P. Let P_M and Λw be the chosen eigenvectors and their corresponding eigen values, respectively.

7- Calculate the projection matrix W as follows:

$$W = HP_M \left(\eta I + \Lambda_W\right)^{\frac{-1}{2}} \qquad ....(16)$$

with I: identity matrix and η: the parameter of regularization.

8- Project the following data X: $Y = W^T X$

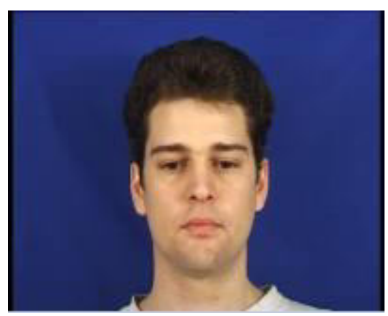
◆ Testing:

1- Project the test feature vector T: T_Fisher = W^T T.

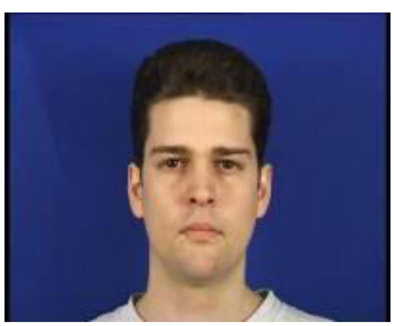
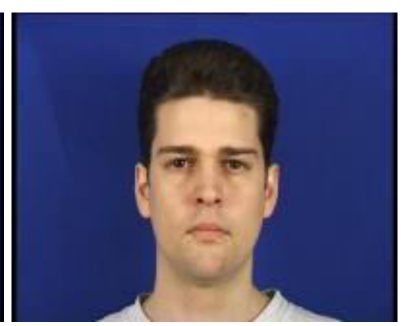
To identify an input test feature vectors, the projected test feature vectors are compared to each projected training feature vectors using the Euclidean distances. The test feature vectors are identified as the closest training image.

2.4 Experimental Results

For the evaluation of the approach presented above, we performed a series of experiments on a sample of the database XM2VTSDB. (Fig 11) shows the results for facial recognition faces belong to two different people and with two variations in the expression.

a) b)

a') b')

c) d)

c’) d’)

Fig11: a) b) c) d): Image requests and a’) b’) c’) d’): Recognized images.

The results obtained, show that the method is effective in the case where there is a little change in the facial expression and pose. On the other hand, our system finds problems in cases where there is a poor detection or mislocalization of characteristics due to illumination or other things that can alter the outcome (beard, hair mustache,.. etc.)

3. CONCLUSIONS AND PERSPECTIVES

In our study, we have proposed a new approach to build a system of facial face recognition. The detection phase is based on the fact that human faces are constructed in the same geometric configuration, and contain regions characterized by a change of a gray level. The combination of these two concepts gives a localization of feature without using color data and regardless of lighting conditions, because we use the color of the skin that presents a robustness overlooked at the small angle of rotation or accessory: mustache, glasses, and beards.

After this phase the recognition is applied only to a vector generated by the Fourier transform of Gabor filters on the face previously detected. The use of the multi-resolution Fourier provides many advantages: it is easy for implementation and resistant to the brightness, facial expression and pose. It allows studying the texture of the face in different directions and scales so that they focus only on spatial frequency exists in the face.