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A Novel Method Using Local and Global Features for Face Recognition

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Abstract

Face recognition is the process of identifying the presence of a face from a database that contains many faces. Face recognition technology has many applications such as Automatic Teller Machine access, verification of credit card, video surveillance etc. The global and local features play an important role for face recognition. In the proposed method, both global and local features are extracted from the input face image. Global features are extracted from whole face images by keeping the low frequency co-efficient of Fast Fourier Transforms. Odd and Even components in the low frequency band are concatenated into single feature vector named Global Fourier Features Vector (GFFV). Local features are extracted by Gabor wavelets. Gabor features are facially grouped into a number of feature vectors named Local Gabor Feature Vector (LGFV). Fisher liner discriminant is applied for both local and global features for classification. The resultant vectors are fused using region based image fusion method. The processed test face image is verified for a match with the faces in the database using Correlation Coefficient and recognition is done.

Keywords: Face Recognition,Fast Fourier Transform, Feature Extraction, Global Features, Image Fusion, Local Features**.**

1. INTRODUCTION

Human face recognition is an important area of image processing. It has important applications in bioinformatics. It is commonly used in applications such as Human-Machine Interfaces (HCI) and automatic access control systems. Face recognition involves comparing an image with a database of stored faces in order to identify the individual of that input image. The related task of face detection has direct relevance to face recognition because images must be analyzed and identified, before they can be recognized. Detecting faces in an image can also help to focus the computational resources of the face recognition system, optimizing the system speed and performance. As one of the most successful applications of image analysis and understanding, face recognition has recently gained significant attention especially during the past several years.

Face recognition is uses for two primary tasks such as Verification and Identification. A face image of an unknown individual along with a claim of identity, ascertaining whether the individual is who he/she claims to be. In Identification of an image of an unknown individual is given, that person’s identity can be determined by comparing that image with the database of images of known individual.

Human face can be characterized both on the basis of local as well as of global feature, Global features are easier to capture they are generally less discriminative than localized features, but are less sensitive to localized changes in the face due to partial deformability of the facial structure. Local features on the face can be highly discriminative, but may suffer for local changes in the facial appearance or partial face occlusion. The optimal face representation should allow to match localized facial features, but also determining a global similarity measurement for the face.

The paper related to this work is organized as follows. Section II describes the state of art, Section III illustrates the implementation of the proposed method. Experimental results are discussed in Section IV and the conclusion is reached in Section V.

2. LITERATURE SURVEY

This section illustrates the literature related to the proposed work. W. Zhao, R. Chellappa, P. Phillips, and A. Rosenfeld [1] surveyed the large number of face recognition algorithms that have been proposed for the past two decades. In the literature of face recognition, there are various face representation methods based on global features, including a great number of sub-space based methods and some spatial frequency techniques. M.Turkand A. Pentland [2] study the principal Component Analysis (PCA), P. Belhumeur, J. Hespanha, and D. Kriegman[3]investigate the Fisher’s linear discriminant (FLD) and M. Bartlett, J. Movellan, and T. Sejnowski [4] investigate the Independent component analysis (ICA),and thay have been widely recognized as the dominant and successful face representation methods. These methods attempt to find a set of basis images from a training set and represent any face as a linear combination of these basis images. J. Lai, P.Yuen, G. Feng[5] and W. Hwang, G. Park, J. Lee, and S. Kee[6] proposed the Spatial-frequency technique of feature exraction using Fourier transform, and Z. Hafed, M. Levine, and M. Savvides[7], J. Heo, R. Abiantun, C. Xie, and B. Kumar[8] investigated the techniques using Discrete Cosine Transform. In this method, face images are transformed to the frequency domain and only the coefficients in the low-frequency band are reserved for face representation. While Global based face representations were popular for face recognition, recently, more and more attempts are made to develop face recognition systems based on local features, which are believed more robust to the variations of facial expression, illumination and occlusion etc., Penve and Atick [9] proposed Local Feature Analysis(LFA) to encode the local topological structure of face images. LFA is considered as a local method as it utilizes a set of kernels to implicitly detect the local structure such as eyes, nose and mouth. A. Timo [10] adopted the local binary pattern (LBP) that is originated from texture analysis for face representation. In this method, LBP operator is first applied and then the resulting LBP “image” is divided into small regions from which histogram features are extracted. The idea of dividing face image is also used in the component based methods, in which the face images are divided into some blocks by a certain rule. Then the image blocks may be taken as inputs of classifiers or given to next step for further feature extraction (e.g., PCA, FLD). Feature extraction means extracting the features from the image so that recognition is made accurate and easy. Both global and local features are crucial for face representation and recognition as suggested by Yu Su, Shiguangshan, Xilin Chen and Wen Gao [11]. Feature extraction can be done by two methods, Global feature extraction and Local feature extraction. Global and local facial features play different roles in face perception. Therefore, it is necessary to combine them together smartly. Intuitively, local information is embedded in the detailed local variations of facial appearance, while global information means the holistically structural configuration of facial organs, as well as facial contour. Thus, from the viewpoint of frequency analysis, global features should mainly correspond to the lower frequencies, while local features should be of high frequency and dependent on position and orientation in the face image. Considering that, global information is represented as the Fourier Coefficients in low frequency band, and local information is encoded as the responses of multiscale and multi orientation Gabor wavelets. However, doing like this is not as computationally desirable as using Fourier transform directly. Specifically, we hope the global features should be compact and orientation-independent. Multiple Gabor wavelets are applied to achieve orientation-independent, thereby computational burden of global feature extraction will increase significantly. In addition, the high dimensionality of Gabor features also brings the problem of “curse of dimensionality” and makes the following process much computationally expensive. That is the reason why Fourier transforms rather than tuned Gabor Wavelet is adopted to extract global features. Rabia Jafri and Hamid R.Arabnia [12] surveyed the various Face recognition techniques and there are three categories: 1.Methods that operate on intensity images. 2. Methods that deal with video sequences. 3. Methods that require the sensory data such as 3D information or infra-red imagery.Lina Zhao, Wanbao Hu, Lihong Cui [14] proposed idea of Feature Comparison Based SVD and FFT.Samra AS, Allah SE, Ibrahim RM[15] worked face recognition using wavelet transform (WT) and fast Fourier transform (FFT). Xiong P, Li G, Sun Y. [16] implemented a face recognition using heat maps. Kim K, Chang FJ, Choi J, Morency LP, Nevatia R, Medioni G [17]implemented a solution using facial landmarks. Chen J, Patel V, Liu L, Kellokumpu V, Zhao G, PietikäinenM[18] propose a robust local descriptor for face recognition.It consist of two components, one based on a shearlet-decomposition andthe other on local binary pattern(LBP). Shearlets can completely analyze the singular structures of piecewise smoothimages, which is useful since singularities and irregular structures carry useful information in an underlying image. In the recent years, deep learning methods [20, 21] have been adapted to the face recognition problem. These methods achieve very good recognition rates and clearly outperform the “standard” algorithms.

3.PROPOSED METHOD

This section describes the proposed method using Local and Global features for face recognition. Global and local facial features play different roles in face perception. In the proposed technique, both local and global features are found and extracted as shown in block diagram Figure 1. Local information is embodied in the detailed local variations of facial appearance while global information means the holistically structural configuration of facial organs as well as facial contour. Global features are extracted from the whole face images by Fast Fourier Transform. Then, the even and odd components of the low frequency band are concatenated to form a single feature vector, called Global Fourier Feature Vector (GFFV).

For local feature extraction, Gabor Wavelet Transform is exploited. Gabor wavelets are used to extract local features at every position of the face image. These features are spatially grouped into a number of feature vectors, each corresponding to a local patch of the face image and called as Local Gabor Feature Vector (LGFV). After the process a face image can be represented by one GFFV and multiple LGFVs. These feature vectors encode diverse discriminatory information. GFFV contains global discriminatory information and each LGFV embodies discriminatory information within certain region.Fisher Linear Discriminant is applied to the vectors of GFFV and LGFVs. The current statistical features used to distinguish faces and non-faces can be divided into two categories such as local features and global features. Some previous global-feature-based face detectors work very well for classifying frontal views of faces, but they are highly sensitive to translation and rotation of the face.

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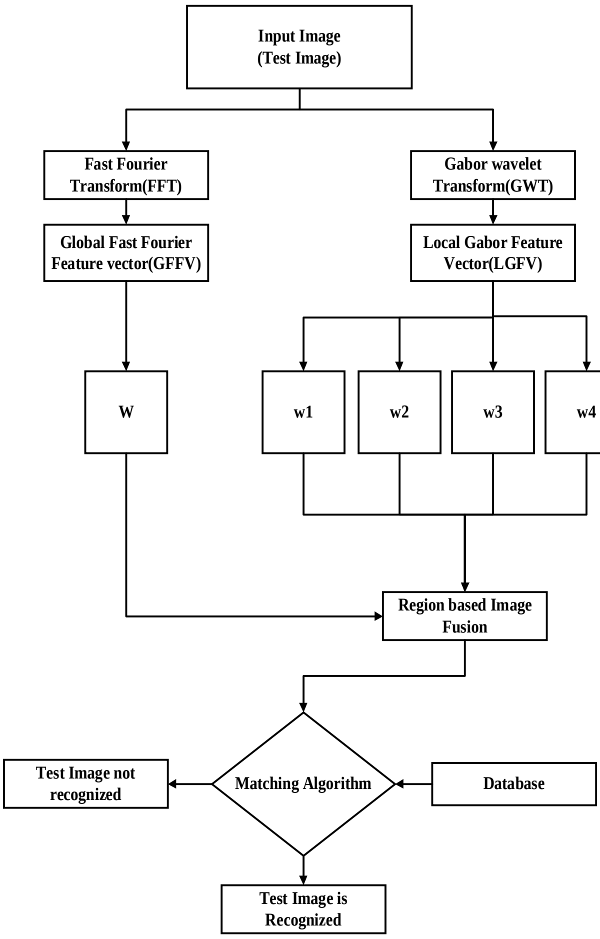

Figure 1: Proposed Technique

Local-feature-based face detectors can avoid this problem by independently detecting parts of the face. For instance, the changes in the parts of the face are small compared to the changes in the whole face pattern for small rotations. So local and global features are both important features. When the non-zero components of a feature are not too much, we call it a sparse feature. The number of nonzero components of a local feature is often largely smaller than the component number of the feature, so it is also a sparse feature. And when the number of non-zero components of a feature becomes larger, it evolves into a global feature.

4.EXPERIMENTAL RESULTS

The proposed algorithm has been tested with standard ORL, Yale and FRGC databases and a few of them are shown in Figure2. The Various steps involved in the experimenting are listed as:

a) Global Feature extraction using FFT.
b) Local Feature extraction using GWT.
c) Identification of Local Patches.
d) Image Fusion using Region based method.
e) Image matching using Correlation Coefficient.

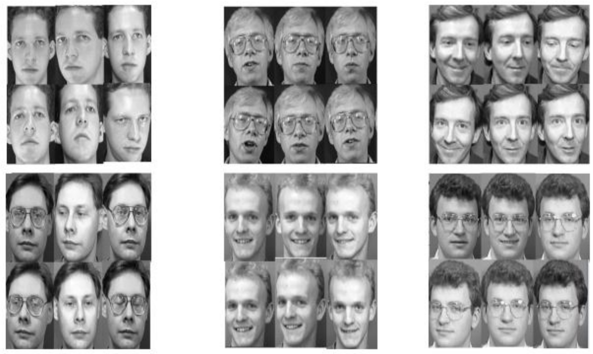

Figure 2. ORL and FRGC Data Base

4.1 Global Feature Extraction using FFT

Fast Fourier transform (FFT) like any other Fourier transform, it transforms the signal or image to its frequency analysis domain which is the best way to represent an image to extract from it the desired features.

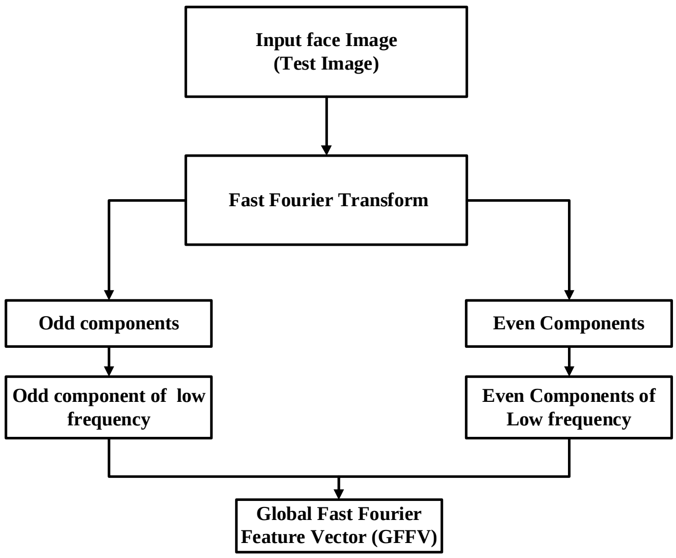

Figure 3. Fast Fourier Feature Vector

Fast Fourier transform is a faster form of discrete Fourier transform (DFT), it has developed by Cooley and Tukey around [13].

While the DFT transform can be applied to any complex valued series, in practice for large series it can take considerable time to compute, the time taken being proportional to the square of the number on points in the series. The computing time for the FFT is proportional N log 2(N). Global features describe the general characteristics of the holistic face and they are often used for the coarse representation. Global information is represented as the Fourier coefficients in low frequency band. Thus, from the frequency point of view global features correspond to low frequency as named Fast Fourier Feature Vector shown in the Figure 3.In global based face representation, each dimension of the feature vector contains the information embodied in every part of the face image, thus corresponds to some holistic characteristic of face. Fast Fourier Transform is adopted for global feature extraction.

4.2 Local Feature Extraction using Gabor Wavelets

Face recognition using Gabor features has attracted considerable attention in computer vision and image processing and pattern recognition. Local information is represented by using Gabor wavelets. For local feature extraction, Gabor wavelets are exploited considering their biological relevance. In contrast, for the local based face representation, each dimension of the feature vector corresponds to merely certain local region in the face, thus only encodes the detailed traits within this specific area. Among various local features, especially, Gabor wavelets have been recognized as one of the most successful local feature extraction methods for face representation. Local features reflect and encode more detailed variation within some local facial regions such as mouth, eyes and nose.

The Gabor wavelet representation facilitates recognition without correspondence because it captures the local structure corresponding to spatial frequency, spatial localization, and orientations selectivity. Gabor wavelets are in many ways like Fourier transform but have a limited spatial domain. 2-D Gabor wavelets are defined in equation (1) as follows:

$$\mu,v^{(Z)} = \frac{k_{\mu,v^2}}{\sigma^2} e^{\left(-k_{\mu,v^2} Z^{\frac{2}{2\sigma^2}}\right)} \left[e^{ik_{\mu,v^z}} - e^{-\sigma^{\frac{2}{2}}}\right] (1)$$

$$K_{\mu,v} = k_v e^{i\emptyset\mu}$$

$$Where\ , k_v \frac{k_{max}}{f^v}\ gives\ the\ frequency\ and$$

$$\emptyset_\mu = \frac{\pi\mu}{8}, \emptyset_\mu \in [0,\pi]$$

$where, \mu$ *and* v *define the orientation and scale of the gabor kernel* $z\ (x,y)$. $K_{\mu,v}$ *is the wave vector* k_{max} *gives the maximum frequency and* f *is the spacing between the kernels in the frequency domain.*

Gabor wavelet consists of a planar sinusoid multiplied by a two-dimensional Gaussian. The sinusoid wave is activated by frequency information in the image. The Gaussian insures that the convolution is dominated by the region of the image close to the center of the wavelet. when a signal is convolved with the Gabor wavelet, the frequency information near the center of the Gaussian is captured and frequency information far away from the center of the Gaussian has a negligible effect. Therefore, compared with Fourier transform which extracts the frequency information in the whole face region, Gabor wavelets only focus on some local areas of the face and extract information with multi-frequency and multi-orientation in these local areas. Gabor wavelets can take a variety of different forms with different scales and orientations as shown Figure 4.

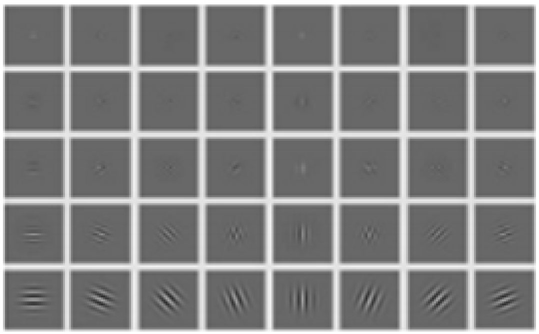

Figure 4: Gabor wavelets of 5 scales and 8 orientations

4.3 Identification of Local Patches from the Images

Gabor features are calculated by convolving Gabor wavelets with the whole face image, it covers all the positions of the face image. Thus, the local information provided by the spatial locations of Gabor features is lost when they are integrated to form one single feature vector. In order to reserve more location information, Gabor features are spatially partitioned into a number of feature sets named Local Gabor Feature Set (LGFS), each of which corresponds to a local patch of the face image as shown in Figure 5.

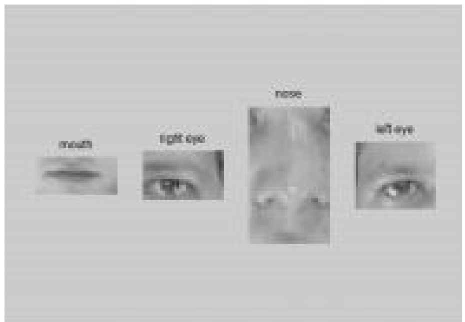

Figure5:Patches from the input image such as mouth, right eye, nose, left eye

Each LGFV is relatively low dimensional, this can greatly facilitate the sequent feature extraction and pattern classification. Human Faces contain some components with fixed high-level semantics such as eyes, nose and mouth. Consequently, the locality information is very meaningful for face modelling. Gabor featuresare spatially grouped into number of feature vectors named Local Gabor Feature Vector (LGFV) as shown Figure 6.

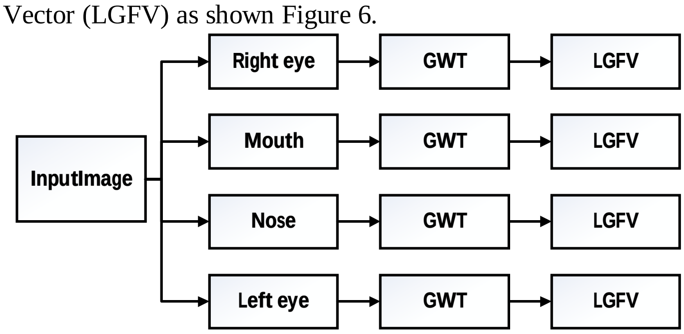

Figure 6: Local Gabor Feature Vector

4.4 Fisher Linear Discriminant (FLD)

A linear classifier is used to identify which class the object belongs by making a classification decision, based on the value of a linear combination of the characteristics. An object's characteristics are also known as feature values and are typically presented to the machine in a vector called a Feature Vector.

FLD is applied to the vectors of GFFV and LGFVs. The current statistical features used to distinguish faces and non-faces can be divided into two categories namely, local features and global features. After feature extraction, N+1 feature vectors are obtained, that is, one global Fourier Feature Vector (GFFV) and N Local Gabor Feature Vectors (LGFVs). Then, N+1 classifiers can be trained by applying FLD to each feature vector. These classifiers are named as component classifiers, opposite to the forthcoming ensemble classifier, i.e., the combination of component classifiers. N+1 Feature vectors contain diverse discriminative information for face recognition. Thus, component classifiers trained on these feature vectors should have certain degree of error diversity. In other words, these component classifiers might agree or disagree with each other when making decision. Considering that the ensemble classifier is generally superior to the single classifier when the predictions of its component classifiers have enough diversity, the component classifiers trained on all the feature vectors are combined into a hierarchical ensemble classifier to improve the recognition accuracy. Hierarchical ensemble method consists of two layers of ensemble: the ensemble of all the local component classifiers, and the ensemble of local classifier and global classifier.

In the first layer, local ensemble classifier (LEC) is obtained by combining N local component classifiers (LCC), each trained on an LGFV, with the number of selected patches. It is formulated as follows equation (2)

$$C_L = \sum_{i=1}^{n} w_{Li} C_{Li} \quad (2)$$

Where, C_L is the local classifier, w_{Li} is the weight of the ith LCC.

In the second layer, the LCC obtained in the first layer is combined with the global classifier (GC) trained on the GFFV to form the hierarchical ensemble classifier (HEC) given by equation (3)

$$C_H = W_G C_G + (1 - w_G) C_L \quad (3)$$

Where, C_H is the ensemble classifier, C_G is the global classifier, W_G is the weight of C_G.

As mentioned previously, global and local features play different roles in face perception. While global features capture the holistic characteristics of the face, therefore, better for coarse representation. local features encode more details in local face areas, therefore, better for finer representation. Considering that, in the proposed method, the input face image is normalized differently for global and local feature extraction. The global Fourier features are extracted from the face image of lower resolution, but covering both external and internal facial features, especially the face contour. On the contrary, the local Gabor features are extracted from the face image of higher resolution, which covers only the internal facial features, e.g., the facial organs. The reason using this strategy lies in the sensitivity of Gabor features to the possible background introduced along with the contour, to which the Fourier features are very robust.

4.5 Image Fusion

Vector Fusion related to a same image or a same object becomes more and more essential in remote sensing applications. It is often necessary to associate additional and/or redundant information, in order to reject, confirm or create a decision. A definition of vector fusion was formulated by Bloch and Maître [19]: "vector fusion is the joint use of heterogeneous information for the assistance with the decision-making".

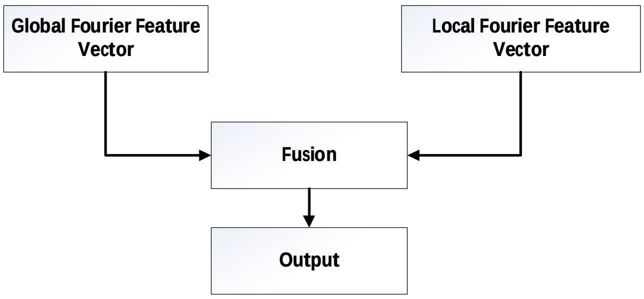

Figure 7: Image Fusion

Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. The image fusion techniques allow the integration of different information sources. Region based image fusion has been utilized. In this fusion method, level decomposing l is always 1. The feature extracted images represent a coarse representation of the original image and may have many inheritedproperties of image. The information can be calculated based on mean intensity or based on some prior information so as to compare the performance of the algorithm. The averaging fusion rule is applied as given in equation (4).

$$Y_s(I) = \frac{Y_A(I) + Y_B(I)}{2} \quad (4)$$

Where, $Y_A(I)$ and $Y_B(I)$ is an approximation coefficient of image A and B respectively. The result of 0 means all information is lost and 1 means all information is preserved. The vector-sum uses, captures and represents the contributions (and properties) of each vectorized dimension because each vector represents the measures, units, and properties of each dimension. This property or ability of each vector arises because each vector's contributions are always accumulated in row sequence and functionally compared in the scatter-plots at each vector's unique and specific phase angle.

4.6 Matching using Correlation Coefficient

The term "correlation" refers to a process for establishing relationships between two variables. A Correlation coefficient measures the strength and direction of a linear association between two variables. One of them does not "causes" the other. Correlation defines that when one variable changes, the other seems to change in a predictable way. A correlation coefficient is a "ratio" not a percent. However, it is very easy to translate the correlation coefficient into a percentage. "Square the correlation coefficient" which means that you multiply it by itself. So, if the symbol for a correlation coefficient is "r", then the symbol for this new statistic is simply r^2 which can be called "r squared". If the dots on the scatter plot tend to go from the lower left to the upper right it means that as one variable goes up the other variable tends to go up also. This is a called a "positive relationship". On the other hand, if the dots on the scatter plot tend to go from the upper left corner to the lower right corner of the scatter plot, it means that as values on one variable go up values on the other variable go down. This is called a "negative relationship". Correlation coefficient of two features x_i ,x_j is given by equation (5)

$$R(i,j) = \frac{C(i,j)}{\sqrt{C(i,i)C(j,j)}} \quad (5)$$

R = corrcoef(X) returns a matrix R of correlation coefficients calculated from an input matrix X whose rows are observations and columns are variables. The matrix R = corrcoef(X) is related to the covariance matrixC= cov (X). The proposed method is evaluated using different databases as shown in the Table 1. The recognition rate of the proposed technique lies above 90% and it is observed that the system is efficient. The table also implies that the False Acceptance Rate (FAR) is very low giving high detection rate shown in Table 1.

Table 1:Recognition rate of proposed technique

Sl. No	Database images tested	No. of input tested	No. of face recognized correctly	Recognition Rate
1	ORL	45	41	88%
2	FRGC	60	55	91%
3	YALE	75	70	93%

5 CONCLUSION

Human beings recognize faces by global and local facial features. In this face recognition method global and local features are extracted by effective Fast Fourier Transform (FFT) and Gabor Wavelet Transform (GWT) respectively. When both the local and global features are utilized the recognition, rate increases than by use single feature alone. The classification errors are reduced using Fisher Linear Discriminant (FLD). The Fusion of the vectors is done by "Region Based Image Fusion". The correlation coefficient is used to match the test image with the database. The proposed method works well compare to other methods. The identification ratio is nearly 90.66 %.

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