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Impact of Kernel Fisher Analysis Method on Face Recognition

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Abstract— ***Human Face recognition is a challenging task in computer vision and pattern recognition. Face recognition is difficult because it is a real world problem. The Human Face is complex, natural object that tends not to have easily identified edges and features. Because of this, it is difficult to develop a mathematical model of that face that can be used as prior knowledge when analyzing a particular image.This paper deals with the correspondence presents Color and Frequency Features based face recognition. The CFF method, which applies an Enhanced Fisher Model (EFM), extracts the complementary frequency features in a new hybrid color space for improving face recognition performance. The new color space, the RIQ color space, which combines the component image of the RGB color space and the chromatic components and of the YIQ color space, displays prominent capability for improving face recognition performance due to the complementary characteristics of its component images. The EFM then extracts the complementary features from the real part, the imaginary part, and the magnitude of the image in the frequency domain. The complementary features are then fused by means of concatenation at the feature level to derive similarity scores for classification. The complementary feature extraction and feature level fusion procedure applies to the I and Q component images as well. The hybrid color space improves face recognition performance significantly, and the complementary color and frequency features further improve face recognition performance. In CFF method particular, the Indian database had used for experimental analysis. There are many problems with face recognition such as facial expression, pose, age and occlusion. The Training set contains 200 images that are either controlled or uncontrolled. The Target set has 400 controlled images and the Query set has 100 uncontrolled images. While the faces in the controlled images have good image resolution, the faces in the uncontrolled images have lower image resolution and . These uncontrolled factors pose grand challenges to the face recognition performance. The face images used in our experiments are normalized to 64×64 to extract the facial region, which contains only face and the performance of face recognition is thus not affected by the factors not related to face, such as hair styles. These experimental results show that the combination of the hybrid color and frequency features by the CFF method is able to further improve face recognition performance. In particular the CFF method achieves the face verification rate (corresponding to the TestSet3) of 80.3% at the false accept rate of 0.1%. Future research will be considerd applying kernel methods, such as the multiclass Kernel Fisher Analysis (KFA) method to replace the EFM method for improving face recognition performance. And Note that the KFA method achieves, at 0.1% false accept rate, 84% face verification rate (FVR) respectively. Experimental result shows that the proposed method is efficient and improves the face recognition performance by large margin***

Keywords— ***KFA(Kernel Fisher Analysis),CFF(Color and Frequency Features based face recognition),EFM, RIQ.***

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I. INTRODUCTION

As one of the most successful applications of image analysis and understanding, face recognition has recently received significant attention, especially during the past several years. At least two reasons account for this trend; the first is the wide range of commercial and law enforcement applications and the second is the availability of feasible technologies after 30 years of research. Even though current machine recognition systems have reached a certain level of maturity, their success is limited by the conditions imposed by many real applications. For example, recognition of face images acquired in an outdoor environment with changes in illumination and/or pose remains a largely unsolved problem. In other words, current systems are still far away from the capability of the human perception system. In addition, the problem of machine recognition of human faces continues to attract researchers from disciplines such as image processing, pattern recognition, neural networks, computer vision, computer graphics, and psychology [19].

1.1 Face Recognition

Face recognition is of great importance in many applications such as identification and verification, employee access to high-security area, human-machine interfaces, law enforcement and automatic crowd surveillance. The main advantage of face recognition as a biometric is its throughput, convenience and non-invasiveness. Most of the research in face recognition has focused on 2D intensity images. However, result from recent studies, FERET (Face Recognition Technology) and the FRVT (Face Recognition Vendor Technology) clearly show that the performance of these traditional 2D face recognition approaches are adversely affected by varying lightning conditions and particularly with respect to varying pose [21], [22].

The human capacity to recognize particular individuals solely by observing the human face is quite remarkable. This capacity persists even through the passage of time, changes in appearance and partial occlusion. Because of this remarkable ability to generate near-perfect positive identifications, considerable attention has been paid to methods by which effective face recognition can be replicated on an electronic level [23]. Certainly, if such a complicated process as the identification of a human individual based on a method as non-invasive as face recognition could be electronically achieved then fields such as bank and airport security could be vastly improved, identity theft could be further reduced and private sector security could be enhanced.

Applications of face recognition are widespread. Perhaps the most obvious is that of human computer interaction. One could make computers easier to use if when one simply sat down at a computer terminal, the computer could identify the user by name and automatically load personal preferences. This identification could even be useful in enhancing other technologies such as speech recognition, since if the computer can identify the individual who is speaking the voice patterns being observed can be accurately classified against the known individual's voice [24].

Human face recognition technology could also have uses the security domain. Recognition of the face could be done of several mechanism employed to identify an individual.

Face recognition as a security measure has the advantage that it can be done quickly, perhaps even in real time, and does not require extensive equipment to implement. It also does not pose as particular inconvenience to the subject being identified, as is the case in retinal scans. It has the disadvantage, however, that it is not a foolproof method of authentication, since human face appearance is subject to various sporadic changes on a day-to-day basis (shaving, hair style, acne, etc…), as well gradual changes over times (aging). Because of this, face recognition is perhaps best used as an augmentation for other identification techniques [27].

A final domain in which face recognition techniques could be useful is search engine technologies. In combination with face detection systems, one could enable users to search for specific people in images. This could be done by either having the user provide as image of the person to be found, or simply providing the name of the person for well-known individuals. A specific application of this technology is criminal mug shot databases. This environment is perfectly suited for automated face recognition since all pose are standardized and lightening and scale are held constant. Clearly, this type of technology could extend online searches beyond the textual clues that are typically used when indexing information [24]

II. RIQ: THE NEW HYBRID COLOR SPACE

Image in the RGB color space consists of the red, green, and blue component images. Other color spaces are calculated from the RGB color space by means of either linear or nonlinear transformations. The complementary characteristics of color spaces can be applied to improve face recognition performance [10][16]. Our research reveals that fusing features across color spaces can enhance the discriminating power of the hybrid color features. As the R component image in the RGB color space is more effective than the luminance [16], we define a new hybrid color space, the RIQ color space, where R is from the RGB color space and I and Q are from the YIQ color space. Our hybrid Color and Frequency Features (CFF) method extracts the complementary frequency features in the new hybrid RIQ color space for improving face recognition performance. It shows the system architecture of the CFF method. First, the R, I and Q component images in the RIQ color space are derived from the RGB color space.

Second, the EFM extracts the complementary frequency features using different masks in the frequency domain from the R, I and Q component images, respectively. Third, the complementary features are fused (by means of concatenation) at the feature level to derive similarity scores for classification. Finally, the similarity scores derived from the R, I and Q images are fused together (through a weighted summation) at the decision level for face recognition. Very recently, the cross-platform acceptance of the International Color Consortium (ICC) color profiling method helped bring uniformity to the picture. It enables the input, output and display devices vendors to transparently, at least to the general user, exchange color data that conform to well characterize color spaces. The color management workflow tools are the latest trend in this development In particular, the set of tools first offered by Adobe in their Photoshop version 5.0.2 program started a new era in the color. Very recently, the cross-platform acceptance of the International Color Consortium (ICC) color profiling method helped bring uniformity to the picture[28].

2.1 Background

Color provides powerful information for object detection, indexing and retrieval. Color histograms and color invariant moments provide robust object recognition against image variations such as illumination. Swain and Ballard developed a color indexing system which applies color histogram for image inquiry from a large image database. The system separates the chrominance from the luminance and the color information derived is invariant to illumination variations [19]. In general, different color spaces, which are defined by means of transformations from the original RGB (red, green, blue) color space, display different color properties. The HSV (hue, saturation, value) color space and its variants, such as the *HSI* (hue, saturation, intensity) color space and the HLS (hue, lightness, saturation) color space, are often applied in locating and extracting facial features It is well known that color spaces provide powerful information for image indexing and retrieval by means of color invariants, color histogram, colortexture, etc [24], [8].

The YCbCr (luminance, Chrominance-blue, Chrominance-red) color space, the YIQ (luminance, in-phase, quadrature) color space, and the YUV color space have wide applications in color clustering and quantization for skin color regions [26] The color information provided by the different color spaces, thus, can be applied for different visual tasks. Skin color, for example, has been used for face detection [13],[12],. A color configuration is defined by an individual or a combination of color component images. Take the RGB color space as an example, possible color configurations are R, G, B, RG, RB, GB, and RGB. Experimental results using 600 FERET color images corresponding to 200 subjects and 456 FRGC (Face Recognition Grand Challenge) color images of 152 subjects show that some color configurations, such as Y V in the Y UV color space and Y I in the Y IQ color. The luminance account for most of the skin color variation and showed that the color histogram based on normalized red and green color components occupies a small cluster in the histogram. On the other hand, showed that the HSV color space and its variations have the advantage of providing large variance among facial features and are suitable for locating and extracting facial features. A nonlinear color transformation to detect skin patches in order to find human faces in an image [22] [26]. However, showed that color information does not improve the face recognition performance in comparison with the intensity information

III. FACE RECOGNITION USING CFF METHOD

3.1 Hybrid color and frequency features (CFF) Method

This section presents our color and frequency features method, or the CFF method, which derives the complementary features in the frequency domain of the component images in the hybrid color space, RIQ Figure. 3.1 show the system architecture of the CFF method. First, the R, I and Q component images in the RIQ color space are derived from the RGB color space. Second, the EFM extracts the complementary frequency features using different masks in the frequency domain from the R, I and Q component images, respectively. Third, the complementary features are fused (by means of concatenation) at the feature level to derive similarity scores for classification. Finally, the similarity scores derived from the R, I and Q images are fused together (through a weighted summation) at the decision level for face recognition.

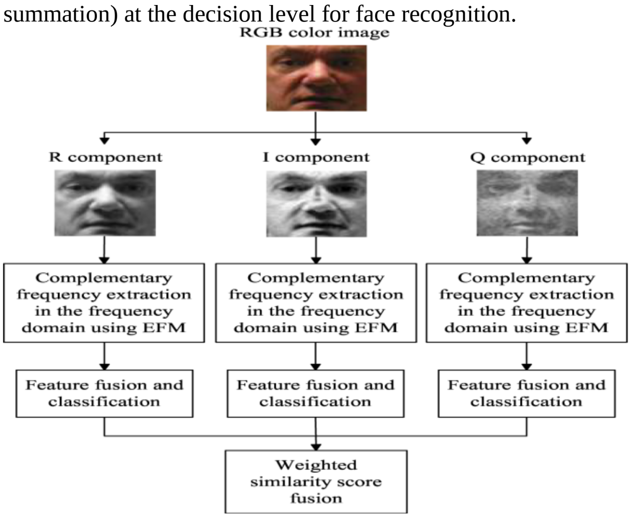

Figure 3.1. System Architecture of the CFF method.

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3.1.1 Frequency Set Selection in the Hybrid Color Space

Fourier transform is able to convert an image from the spatial domain to the frequency domain, where the image is decomposed into the combination of various frequencies. Applying this technique, one can extract the salient image properties in the frequency domain that are often not available in the spatial domain. Figure.3.2 shows the 2-D discrete Fourier transform of a face image: the real part (log plot), the imaginary part, and the magnitude (log plot). The last image in Figure. 3.2 defines a mask (the gray area), which is used to extract the face information in the Fourier domain. Before extracting the hybrid color and frequency features, we perform data reduction by means of frequency set selection of the real part, the imaginary part, and the magnitude in the frequency domain. Fig. 4 shows a mask of size n× 2n. $M_{n\times 2n}$ which is defined as the gray sub-region that extracts the frequency features of the real part, the imaginary part, and the magnitude from the right two quadrants. As the face images in our research have the spatial resolution of 64×64, the real part, the imaginary part, and the magnitude in the frequency domain have the same resolution of 64×64.

Figure 3.2 Two-Dimensional Discrete Fourier Transform of a Face Image :The Real part(log plot),the Imaginary part, and the Magnitude in Fourier domain

In the hybrid color space, the R,I and Q component images apply some different masks to extract their frequency features, respectively. In particular, Figure. 3.3 shows that the R component image first applies two masks, $M_{8\times 16}$ and $M_{32\times 64}$, to extract the frequency features from the real and the imaginary parts, respectively, and then utilizes the mask, $M_{32\times 64}$, to extract the frequency features from the magnitude in the frequency domain. The frequency features extracted corresponding to these masks are $X^R_{r,8\times 16}$, $X^R_{i,8\times 16}$, $X^R_{r\,32\times 64}$ $X^R_{i\,32\times 64}$ and $X^R_{m,32\times 64}$ respectively. After reshaping and concatenating the real and imaginary features there are three frequency pattern vectors resulting from the R component image: $X^R_{ri,\,256\times 1}$, $X^R_{ri,\,4096\times 1}$, and $X^R_{m,\,2048\times 1}$. Figure 3.3 also revels that the I component image first applies three masks $M_{32\times 64}$, $M_{29\times 58}$ and $M_{27\times 54}$, to extract the frequency features from the real and the imaginary parts, respectively. And then applies the mask, $M_{32\times 64}$,to extract the frequency features from the magnitude in the frequency domain.The frequency features extracted corresponding to these three masks are $X^I_{r,\,32\times 64}$, $X^I_{i,\,32\times 64}$, $X^I_{r\,,29\times 58}$, $X^I_{i\,,29\times 58}$, $X^I_{r\,,27\times 54}$, $X^I_{i\,,27\times 54}$ and $X^I_{m\,,32\times 64}$, respectively. After reshaping and concating the real and imaginary featurs, there are four frequency pattern vectors resulting from the I component image : $X^I_{ri,\,4096\times 1}$, $X^I_{ri,\,3364\times 1}$, $X^I_{ri\,,2916\times 1}$ and $X^I_{m\,,2048\times 1}$ similarly.The four frequency pattern vectors resulting from the Q component image are as follows: $X^Q_{ri,\,4096\times 1}$, $X^Q_{ri,\,3364\times 1}$, $X^Q_{ri\,,2916\times 1}$ and $X^Q_{m\,,2048\times 1}$

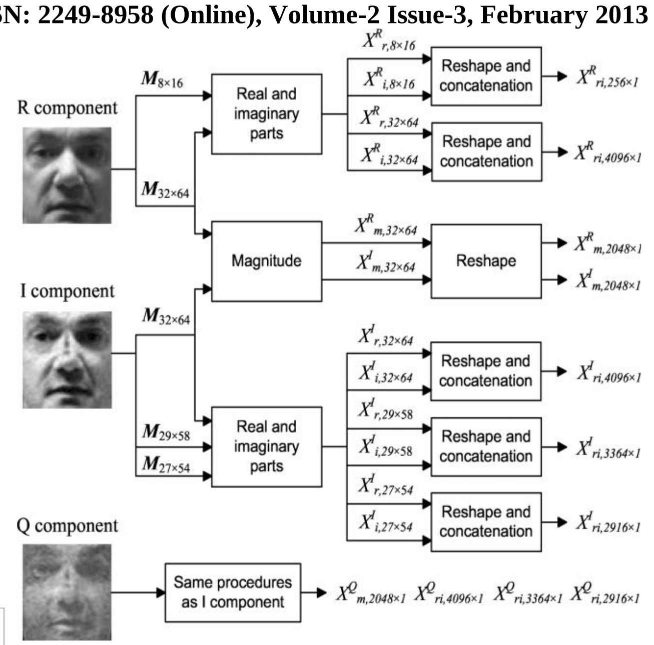

Figure 3.3 Frequency Pattern Vectors by means of Frequency set selection in the Hybrid Color space

3.1.2 Hybrid Color and Frequency Extraction

The frequency pattern vectors derived in the hybrid color space are further processed using the EFM method [12] to extract the hybrid color and frequency features. Next we briefly review the EFM method and then apply it for feature extraction. The EFM method first applies PCA to reduce the dimensionality of the input pattern vector. Let X € RN be a random vector representing a frequency pattern vector. The new pattern vector with reduced dimensionality by means of PCA may be derived as follows:

$$Y=[\phi 1\ \phi 2 \ldots\ldots \phi m]\ tx \qquad (3.1)$$

where $\phi 1\ \phi 2 \ldots\ldots \phi m$ (m < N) are the eigenvectors corresponding to the largest eigenvalues of the covariance matrix of X. The reduced pattern vector _, however, contains only the most expressive features that are not suitable for pattern classification. One solution to this problem is to apply the Fisher linear Discriminant FLD, to achieve high Separability among the different pattern classes [6].

3.2 Enhanced Fisher Model Method.

The EFM method further processes the frequency pattern vectors derived in the hybrid color space to extract the hybrid color and frequency features. Taking the R component image as an example, we next show the procedure about how to extract, fuse, and classify the hybrid color and frequency features. Fig.3.4 shows the hybrid color and frequency feature extraction, fusion, and classification for the R component image using the EFM method. Specifically, after the frequency set selection and feature concatenation, we have three frequency pattern vectors resulting from the R component image: and These frequency pattern vectors are then processed by the EFM to extract the low-dimensional EFM features. The three EFM feature vectors are fused by means of concatenation to form another feature vector. This fused EFM feature vector is further processed by the EFM to derive the final feature vector for the computation of the similarity scores.

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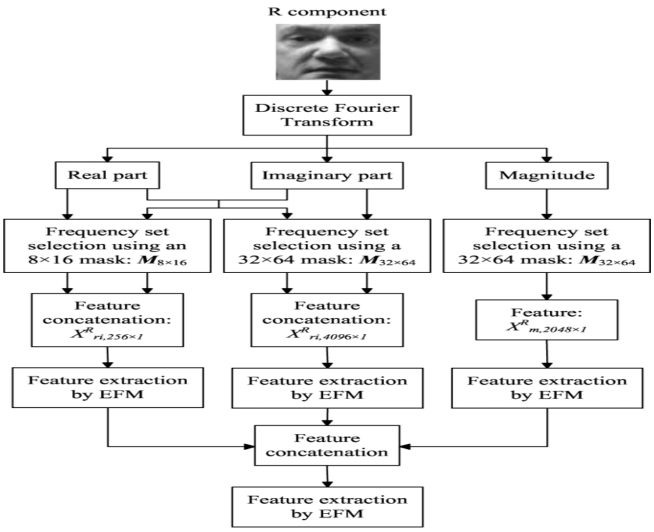

Figure 3.4 Hybrid Color and Frequency Feature Extraction, Fusion, and Classification for the R Component Image using EFM method

3.3 KFA Algorithm

The KFA method, however, manages to compute the inner products by means of a kernel function:

$$k(x, y) = (\Phi(x).\ \Phi(y) \qquad (3.2)$$

For a function to be a kernel function, it has to satisfy the Mercer's condition [10], [6]: Definition (Kernel Function). A sufficient and necessary condition for a symmetric function to be a kernel function is that its Gram matrix is positive semi definite. Three classes of widely used kernel functions are the polynomial kernels, the Gaussian or RBF kernels, and the sigmoid kernels [12]:

$$k(x, y) = (x\ .\ y)^{d,} \qquad (3.3)$$

Where ,k(x,y) is the kernel function x and y are the input space

$$k(x, y) = \exp\ (- \|x\text{-}y\|^2 / 2\sigma^2), \qquad (3.4)$$

Where ,k(x,y) is the Gaussian or RBF kernels , σ is the sigmoid kernels

$$k(x, y) = \tanh(k(x\ .\ y) + \theta), \qquad (3.5)$$

Where, k(x,y) is the sigmoid kernels x and y are the input space Where, $d\ \varepsilon\ N$, $\sigma > 0$, $k > 0$, and $\theta < 0$.Note that the sigmoid kernels (see (19)) do not actually define a positive semi-definite Gram matrix, hence are not kernel functions by definition [10] .Nevertheless, the sigmoid kernels have been successfully used, in practice, such as in building support vector machines [38]. To further improve pattern classification performance, the KFA method introduces and applies the following fractional power polynomial models:

$$k(x\ .\ y) = \text{sign}\ (x\ .\ y)\ (\text{abs}(x\ .\ y)^d, \qquad (3.6)$$

Where k(x . y) is the fractional power polynomial. sign (.) is the sign function, And abs(.) computes the absolute value, and $0 < d < 1$.

Note that a fractional power polynomial does not necessarily define a kernel function as it might not define a positive semi definite Gram matrix [10]. A fractional power polynomial is therefore called a model rather than a kernel. The application of the fractional power polynomial models is largely motivated by the successful applications of the sigmoid kernels in practice, which are not kernel functions by definition. The KFA Algorithm steps as follows:

1. Choose a kernel function k(x . y) (see (3), (4), and (5)) or fractional power polynomial model(see (20)).
2. Center the training data in the feature space (see [10] for centering data in the feature space).
3. Compute the kernel matrix K using the centered training data and the kernel function or the fractional power polynomial model .
4. Compute the bloc diagonal matrix, the W matrix.
5. Solve the eigenvalue problem of (12) and choose n eigenvectors, α_1, α_2, …….,α_n, Corresponding to the largest eigenvalues. Note that the small positive regularization number is empirically chosen, such as 0.001.
6. Normalize the eigenvectors α_1, α_2, ……,α_n, by means of and derive the matrix A.
7. Subtract the grand mean of the training data from every test (gallery/target or test Image/query) sample in the feature space.
8. Compute the vector B for every test sample using the kernel function or the fractional power polynomial model introduced in Step 1.
9. Compute the KFA features of the test sample using A and B: $F = A^t B$.

The Eigen vectors are calculated from the input sample of each respective image. Then the average mean is evaluated from the input sample. Then this data is used to the face analysis with the input image form the still images. The kernel Fisher analysis, or the KFA method, derives a unique solution for multiclass pattern classification problems based on a discriminant analysis criterion in the high-dimensional feature space. Let w_1, w_2 …..,w_L and N_1, N_2, . . .,N_L denote the classes and the number of samples within each class, respectively. Let X_1,X_2, . . . ,X_M ε IR^N be the training samples in the input space and Φ be a nonlinear mapping between the input space and the feature space: Φ:IR^N ε F. Assume the mapped data is centered for centering data in the feature space and let D represent the data

3.3.1. Face Recognition Using KFA

The multiclass Kernel Fisher Analysis method to replace the EFM method for improving faces recognition performance. The KFA method achieves, at 0.1% false accept rate, 84% FVR.

Implementation of KFA is as follows.

1) Generating the data set space matrix
2) Generating the kernel matrix K
   K= D*D
3) Generating the block diagonal matrix W
   W= blkdiag (K)
4) Finding the eigen vector and eigen values
   [V, D]=eigs (W)
5) Normalizing the eigen vectors with factor 0.001
   (kk+e I)-1 (kwk) = β
6) Generating A matrix
   A= β *V
7) Generating matrix D by subtracting mean from it
   D=D-mn
8) Generating matrix K
   K= D*D'
9) Generating block diagonal matrix W
   W= blkdiag (K)
10) Generating eigen values and eigen vector
   [V2, D]=eigs (W)
11) Normalizing of eigen vector using 0.001
   (kk+e I)-1 (kwk) = β
12) Generating matrix B
   BA= β *V2
13) Generating KFA matrix F
   F=A'*B

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3.4 Euclidean distance as classifier for face recognition

The Euclidian distance classifier is an efficient classification technique in area where clusters of points representing the different entities to be classified are spaced far apart in feature space. The idea behind the Euclidian distance classifier is that one computes the average of several training vectors for each possible categorization and then classifies a given test vector by determining to which cluster the average is the vector nearest. The results for the Euclidian distance classifier are remarkable pleasing. The Euclidean distance between points, P=(p1,p2,p3,p4….,pn) and Q = (q1,q2,q3,q4…,qn) , in Euclidean n-space is defined as

$$\sqrt{\sum_{i=1}^{n}(Pi-Qi)}$$

3.5 Experiments on color Indian Database

In this Section, the performance of the face recognition system as a whole is examined. Tests are carried out to confirm that face recognition can perform accurately as a biometric for recognition of individuals. As well as confirming that the system provides accurate recognition, experiments are conducted in order to confirm the distinctiveness of human face pattern. The stepwise results obtained from the face recognition system are as follows:

Image Acquisition: The database contains a set of face images taken in February, 2002 in the IIT Kanpur campus. There are eleven different images of each of 40 distinct subjects. For some subjects, some additional photographs are included. All the images were taken against a bright homogeneous background with the subjects in an upright, frontal position. The files are in JPEG format. The size of each image is 640x480 pixels, with 256 grey levels per pixel. The images are organized in two main directories - males and females. In each of these directories, there are directories with name as a serial numbers, each corresponding to a single individual. In each of these directories, there are eleven different images of that subject, which have names of the form abc.jpg, where abc is the image number for that subject. The following orientations of the face are included: looking front, looking left, looking right, looking up, looking up towards left, looking up towards right, looking down. Available emotions are: neutral, smile, laughter, sad/disgust

Figure 3.5 INDIAN Database: face images

IV. PERFORMANCE EVALUATION (FAR, FRR)

A recognition system may be employed in different scenarios: the most common are verification, identification and watch list. In the verification scenario the face of a subject is acquired and the subject claims its identity; the system must determine whether the claimed identity matches the true identity of the subject. A subject that claims his true identity is called a client, otherwise he is an imposter. In the identification scenario the system takes a face and must indicate the identity of the subject; to be able to do so the subject must have been previously registered in the gallery of known subjects through an enrollment procedure. The watch list scenario is a refinement of the identification scenario; if the subject is not enrolled, the system states that his identity is unknown.

The performance evaluation techniques are specific techniques are specific for each application scenario, but all the methods are based on the analysis of one or more similarity matrix, obtained by a scoring step (1). The scoring phase considers two set of faces: one called the gallery contains a template for each known subject: the other is a set of test images which will be matched against each element of the gallery. Given n test images of identities $p_1,\ldots\ldots\ldots p_n$ and a gallery of m subject of identities $g_1,\ldots\ldots\ldots g_m$, the scoring phase produces a n x m similarity matrix S whose elements are the similarities between an element of the gallery and a test image (Sy is the similarity between the i-th test image and the j-th element of the gallery). The subsections here below introduce the principal performance evaluation techniques for the verification and identification scenario.

4.1 Verification

Verification is performed by computing the similarity between the test image and the template corresponding to the claimed identity. If that similarity is greater than a given threshold, the identity is confirmed and the test image accepted, otherwise the test image is rejected. The behavior of a verification system is thus controlled by a threshold t, whose optimal value determined by domain issues.The main tools for the evaluation of verification systems are the False Acceptance Rate (FAR), and the False Rejection Rate (FRR), which can be easily computed. The FRR is the fraction of clients rejected by the system. The indices are computed considering all the possible combinations of elements in the gallery and test images. In other words, for all the n test images m verification test are performed, claiming every time a different identity. A good verification system will be characterized by low values of both FAR and FRR. The FAR does not decrease with respect to threshold t, while the FRR does not increase, so there is a trade-off between the two error rates: the improvement of one of them produces an increment of the other. The determination of the optimal value for t is usually the last step in experimentation. However, it is often useful investigate the characteristics of the algorithm independently of domain-specific issues. The main tool for this is the ROC curve (Receiver Operator Characteristic), which consists of a parameter is plot of the FAR and FRR error rates, obtained by varying the threshold. Two or more verification systems, or different versions of the same system, can be compared by drawing the corresponding ROC curves on the same plot.

4.2 Identification

The objective in the identification scenario is to determine of the identity of a subject when presented with a test image. The face image must be known to the system. Identification is performed by considering the similarity values between the test images and all the templates in the gallery. The identity chosen will be that with the highest similarity. The evaluation of an identification system is simpler than the analysis of a verification system. The most important measure of the performance of an identification system is the identification Rate (IR), i.e. the fraction of test images that are correctly identified.

I FAR: False Accept Rate

The probability that biometric system will incorrectly identify an individual or will fail to reject an imposter.The FAR of this Face Recognition System is 0 to 4%

II.FRR: False Reject Rate

The False Reject Rate of this Face Recognition System is 0 to 5%

4.3 Results

The Query image is given as input to the face recognition system, then face recognition system display the message image is present in the database otherwise display as message image is not present in the database.

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Table 4.1 Face Verification Rate at 0.1% False Accept Rate of the Color Component Images. RIQ and YIQ color space

Color component/space	FVR (Test Set 1)	FVR (Test Set 2)	FVR (Test Set 3)
R	56%	58%	60%
Y	52%	56%	56%
I	44%	48%	50%
Q	52%	50%	46%
YIQ	68%	74%	76%
RIQ	74%	76%	78%

Face verification rate are calculated from Test Set 1,Test Set 2 and Test Set 3 for the color component R , Y, I, Q ,YIQ and RIQ Images. Test Set 1, Test Set 2 and Test Set 3 contain the 20 images each. And the face verification rate is increased according to Test Set 1, Test Set 2 and Test Set 3. YIQ and RIQ color space in particular, the EFM method first process each individual component image to derive discriminating features. Table 4.1 shows that 1) the R component image possesses more discriminating capability then the Y component. 2) Fusion of individual color component images boosts the face verification performance significantly and 3) the RIQ Color space achieves better face verification performance then the YIQ color space

Table 4.2 Face Verification Rat at 0.1% False Accept Rate of the

Methods	FVR (Test Set 1)	FVR (Test Set 2)	FVR (Test Set 3)
Hybrid Color and Frequency Feature method	**60%**	**70%**	**80%**
Kernel Fisher Analysis method (KFA)	**80%**	**84.33%**	**88.96%**

Color Componen Image before and after illumination normalization In table 4.2 Set an illumination normalization procedure for improving face recognition performance. The result shows of the R, I and Q component images using the illumination normalization procedure helps the R (but not the I and Q) Component image for alleviating the effect of illumination variations. Illumination normalization helps improve face recognition performance for the original R component image.

Table 4.3 Face Verification Rate at 0.1% False Accept Rate of the R,I and Q Frequency Features. And the New CFF method.

Color component /space	Original Image	Normalize Image
R	60%	62%
I	50%	36%
Q	46%	14%

Face verification rate at 0.1% false accept rate of the R, I and Q frequency features .At the decision level, rather than fusing the three similarity matrices by means of a simple summation, we take in to consideration of the different contribution by the three component images in the hybrid color space .Table 4.3 shows the performance of the frequency features extracted from the individual component images in the RIQ hybrid color space and their fused result R_{norm} and R_{orig} represent the frequency features extracted from the illumination normalized and the origin R component image respectively. CFF_{orig} and CFF_{norm} represent the fusion of the corresponding R frequency features with the I and Q frequency features respectively. This shows that the illumination normalization helps improve face recognition performance for both the original R component image and the frequency features extracted from the R image.

Table 4.4 Comparative Analysis between CFF and KFA

	Criss Cross Unit cell			3x3 array of Criss Cross cell
	S11 (dB)	f_r (GHz)	DNG band. (GHz)	DNG band (GHz)
Dupont ($\varepsilon_r = 7.8$)	34	5.6	5 to 6	10
RT Duroid ($\varepsilon_r = 2.2$)	-51.8	8.7	6.5 to 9	4 to 7
FR4 ($\varepsilon_r = 4.4$)	-30	7	6 to 7	4.5 to 6

Comparative analysis between hybrid color and frequency features method (CFF) and the kernel fisher analysis method (KFA) shows that the average face verification rate for the sample of test set 1, test set 2 and test set 3 are 70% and 84.33%

4.4 Comparative Analysis between Original image and Normalize image

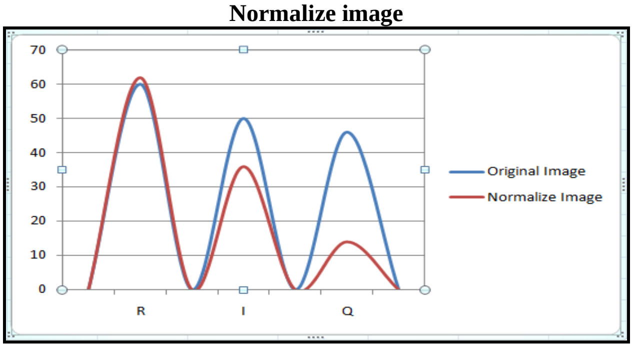

Figure 4.1 Face Verification Rate at 0.1% False Accept Rate of the Color Component image R, I and Q

Figure 4.1 shows the Result graph of the R, I and Q component images using the illumination normalization procedure .these result show that the normalization procedure helps the R but not the I and Q component image for alleviating the effect of illumination variation. In figure face verification graph of R and Q component rising its means illumination normalization procedure helps the R (but not the I and Q) Component image for alleviating the effect of illumination variations. Illumination normalization helps improve face recognition performance for the original R component image.

4.5 Comparative Analysis of CFF and KFA

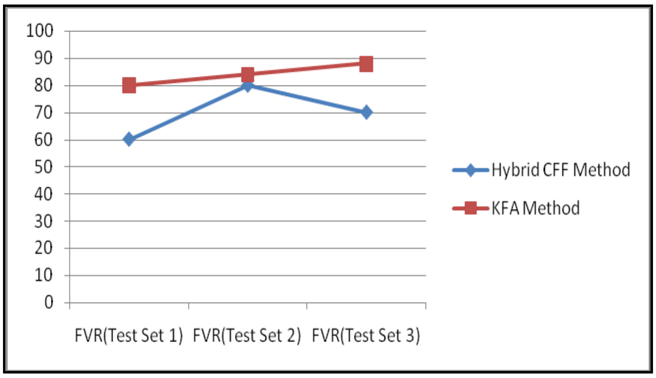

Figure.4.2 Comparative Analysis of CFF and KFA

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Figure 4.2 shows the .Face verification rate (FVR) for KFA method for the sample of test set 1, test set 2 and test set 3 are 80% , 84.33% and 88.96% and similar for Hybrid CFF method are 60% , 80% and 70 % so this shows that average face verification performance of KFA(84.33%) is greater than the CFF method(70%). Face recognition performance is improved in KFA method than CFF method

V. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion:

This paper gives a generalization of CFF which perform significantly better than PCA, LDA, and their variants. This work introduced the new class-dependence feature analysis (CFA) method that computes only inner products and uses the generic datasets. The basic CFA method yield very good verification rates on the INDIAN database data. Fourier transform is able to convert an image from the spatial domain to the frequency domain, where the image is decomposed into the combination of various frequencies. Applying this technique, one can extract the salient image properties in the frequency domain that are often not available in the spatial domain. The CFF method, which applies an Enhanced Fisher Model (EFM), extracts the complementary frequency features in a new hybrid color space for improving face recognition performance. The new color space, the RIQ color space, which combines the R component image of the RGB color space and the chromatic components I and Q of the YIQ color space, displays prominent capability for improving face recognition performance due to the complementary characteristics of its component images.

In CFF method, the Indian database is used for experimental analysis. There are many problems with face recognition such as illumination, light variation, facial expression, pose, age and occlusion. The face images used in our experiments are normalized to 64×64 to extract the facial region, which contains only face and the performance of face recognition is thus not affected by the factors not related to face, such as hair styles. The experimental analysis shows that Euclidian distance classifier is the best classifier.Comparative analysis show that the combination of the hybrid color and frequency features by the CFF method is able to improve face recognition performance. In particular the CFF method achieves the face verification rate (corresponding to the TestSet3) of 80.3% at the false accept rate of 0.1% The KFA method achieves, at 0.1% false accept rate, 84% face verification rate (FVR).

5.2 Future scope:

In this work face recognition performance for the color frequency and feature method is less. The frequency pattern vectors derived in the hybrid color space are further processed using the EFM method. The reduce pattern vector Y, however, contain only the most expressive features that are not suitable for pattern classification. After the transformation from the RGB color space, the I component image often display sharper contrast around the eye and the mouth corner regions then the R component image does. The experimental result shows that the normalization procedure helps the R but not the I and Q component image.

Kernel Fisher Analysis method is to replace the EFM method for improving face recognition performance. The most expressive features are suitable for pattern classification by applying the fisher linear discriminant or FLD to achieve high separability among the different pattern classes. The EFM addresses the over fitting problem and displays the enhanced generalization performance [11]. The proposed face recognition system works satisfactory on still images .There is tremendous future scope for face recognition system .this work can be extended for video images. The video surveillance is need of current era, thus the video surveillances most growing task, an embedded system for face recognition, which provides high-end security, can be design in future. In future home, offices, industries, education institutes, government system and defense system will require an authentication system for identification as well as verification. The most popular, feasible and effective will be a generalized embedded face recognition system, which will serve as multipurpose system at every place.

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