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Analysis Of Face Recognition- A Case Study On Feature Selection And Feature Normalization

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Abstract

In this the effects of feature selection and feature normalization to the face recognition scheme is presented. From the local features that are extracted using block-base discrete cosine transform (DCT), three feature sets are derived. These local feature vectors are normalized in two different ways by making them unit norm and by dividing each coefficient to its standard deviation that is learned from the training set. In this work use local information by using block based discrete cosine transform. Here the main idea is to mitigate the effects of expression, illumination and occlusion variations by performing local analysis and by fusing the outputs of extracted local features at the feature and at the decision level.

Keywords- *Image Processing, DCT, Face recognition;*

I. INTRODUCTION

Face recognition has been an active research area over the last 30 years. Scientists from different areas of psychophysical sciences and those from different areas of computer sciences have studied it. Psychologists and neuroscientists mainly deal with the human perception part of the topic, whereas engineers studying on machine recognition of human faces deal with the computational aspects of face recognition. Face recognition has applications mainly in the fields of biometrics, access control, law enforcement, and security and surveillance systems. Biometrics is methods to automatically verify or identify individuals using their physiological or behavioral characteristics [1-4].

A. Human Face Recognition

When building artificial face recognition systems, scientists try to understand the architecture of human face recognition system. Focusing on the methodology of human face recognition system may be useful to understand the basic system. However, the human face recognition system utilizes more than that of the machine recognition system which 7 is just 2-D data. The human face recognition system uses some data obtained from some or all of the senses visual, auditory, tactile, etc. All these data is used either individually or collectively for storage and remembering of faces. In many cases, the surroundings also play an important role in human face recognition system. It is hard for a machine recognition system to handle so much data and their combinations. However, it is also hard for a human to remember many faces due to storage limitations. A key potential advantage of a machine system is its memory capacity [1-4], whereas for a human face recognition system the important feature is its parallel processing capacity. The issue "which features humans use for face recognition" has been studied and it has been argued that both global and local features are used for face recognition. It is harder for humans to recognize faces, which they consider as neither "attractive" nor "unattractive". The low spatial frequency components are used to clarify the sex information of the individual whereas high frequency components are used to identify the individual. The low frequency components are used for the global description of the individual while the high frequency components are required for finer details needed in the identification process. Both holistic and feature information are important for the human face recognition system. Studies suggest the possibility of global descriptions serving as a front end for better feature-based perception [1-4]. If there are dominant features present such as big ears, a small nose, etc. holistic descriptions may not be used. Also, recent studies show that an inverted face (i.e. all the intensity values are subtracted from 255 to obtain the inverse image in the gray scale) is much harder to recognize than a normal face. Hair, eyes, mouth, face outline have been determined to be more important than nose for perceiving and remembering faces. It has also been found that the upper part of the face is more useful than the lower part of the face for recognition. Also, aesthetic attributes (e.g. beauty, attractiveness, pleasantness, etc.) play an important role in face Recognition; the more attractive the faces are easily remembered.

For humans, photographic negatives of faces are difficult to recognize. But, there is not much study on why it is difficult to recognize negative images of human faces. Also, a study on the direction of illumination showed the importance of top lighting it is easier for humans to recognize faces illuminated from top to bottom than the faces illuminated from bottom to top. According to the neurophysicists, the analyses of facial Expressions are done in parallel to face recognition in human face recognition system. Some prosopagnosic patients, who have difficulties in identifying familiar faces, seem to recognize facial expressions due to emotions. Patients who suffer from organic brain syndrome do poorly at expression analysis but perform face recognition quite well.

B. Machine Recognition of Faces

Human face recognition were expected to be a reference on machine recognition of faces, research on machine recognition of faces has developed independent of studies on human face recognition. During 1970's, typical pattern classification techniques, which use measurements between features in faces or face profiles, were
Used. During the 1980's, work on face recognition remained nearly stable. Since the early 1990's, research interest on machine recognition of faces has grown tremendously. The reasons may be:

- An increase in emphasis on civilian/commercial research projects,
- The studies on neural network classifiers with emphasis on real-time computation and adaptation,
- The availability of real time hardware.
- The growing need for surveillance applications.

a. Statistical Approaches

Statistical methods include template matching based systems where the training and test images are matched by measuring the correlation between them. Moreover, statistical methods include the projection-based methods such as Principal Component Analysis (PCA), Linear Discriminator Analysis (LDA), etc. In fact, projection based systems came out due to the shortcomings of the straightforward template matching based approaches; that is, trying to carry out the required classification task in a space of extremely high dimensionality *Template Matching:* Brunelli and Poggio [3] suggest that the optimal strategy for face recognition is holistic and corresponds to template matching. In their study, they compared a geometric feature based technique with a template matching based system. In the simplest form of template matching, the image (as 2-D intensity values) is 11 compared with a single template representing the whole face using a distance metric. Although recognition by matching raw images has been successful under limited circumstances, it suffers from the usual shortcomings of straightforward correlation-based approaches, such as sensitivity to face orientation, size, variable lighting conditions, and noise. The reason for this vulnerability of direct matching methods lies in their attempt to carry out the required classification in a space of extremely high dimensionality. In order to overcome the curse of dimensionality, the connectionist equivalent of data compression methods is employed first. However, it has been successfully argued that the resulting feature dimensions do not necessarily retain the structure needed for classification, and that more general and powerful methods for feature extraction such as projection based systems are required. The basic idea behind projection-based systems is to construct low dimensional projections of a high dimensional point cloud, by maximizing an objective function such as the deviation from normality.

b. Face Detection and Recognition by PCA

The Eigenface Method of Turk and Pentland [5] is one of the main methods applied in the literature, which is based on the Karhunen-Loeve expansion. Their study is motivated by the earlier work of Sirowich and Kirby [6], [7]. It is based on the application of Principal Component Analysis to the human faces. It treats the face images as 2-D data, and classifies the face images by projecting them to the eigenface space, which is composed of eigenvectors obtained by the variance of the face images. Eigenface recognition derives its name from the German prefix *Eigen*, meaning own or individual. The Eigenface method of facial recognition is considered the first working facial recognition technology. When the method was first proposed by Turk and Pentland [5], they worked on the image as a whole. Also, they used Nearest Mean classifier two classify the face images. By using the observation that the projection of a face image and non-face image are quite different, a method of detecting the face in an image is obtained. They applied the method on a database of 2500 face images of 16 subjects, digitized at all combinations of 3 head orientations, 3 head sizes and 3 lighting conditions. They conducted several experiments to test the robustness of their approach to illumination changes, variations in size, head orientation, and the differences between training and test conditions. They reported that the system was fairly robust to illumination changes, but degrades quickly as the scale changes [5]. This can be explained by the correlation between images obtained under different illumination conditions the correlation between face images at different scales is rather low. The eigenface approach works well as long as the test image is similar to the training images used for obtaining the eigenfaces.

C. Face Recognition by LDA

Etemad and Chellappa [8] proposed a method on appliance of Linear/Fisher Discriminant Analysis for the face recognition process. LDA is carried out via scatter matrix analysis. The aim is to find the optimal projection which maximizes between class scatter of the face data and minimizes within class scatter of the face data. As in the case of PCA, where the eigenfaces are calculated by the eigenvalue analysis, the projections of LDA are calculated by the generalized eigenvalue equation.

Subspace LDA*:* An alternative method, which combines PCA and LDA is studied. This method consists of two steps the face image is projected into the eigenface space, which is constructed by PCA, and then the eigenface space projected vectors are projected into the LDA classification space to construct a linear classifier. In this method, the choice of the number of eigenfaces used for the first step is critical; the choice enables the system to generate class separable features via LDA from the eigenface space representation. The generalization/over fitting problem can be solved in this manner. In these studies, a weighted distance metric guided by the LDA eigenvalues was also employed to improve the performance of the subspace LDA method.

II. BACKGROUND INFORMATION

Most research on face recognition falls into two main categories feature-based and holistic. Feature-based approaches to face recognition basically rely on the detection and characterization of individual facial features and their geometrical relationships. Such features generally include the eyes, nose, and mouth. The detection of faces and their features prior to performing verification or recognition makes these approaches robust to positional variations of the faces in the input image. Holistic or global approaches to face recognition, on the other hand, involve encoding the entire facial image. Thus, they assume that all faces are constrained to particular positions, orientations, and scales[10-14].

Feature-based approaches were more predominant in the early attempts at automating the process of face recognition. Some of this early work involved the use of very simple image processing techniques (such as edge detection, signatures, and so on) for detecting faces and their features. In this approach an edge map was first extracted from an input image and then matched to a large oval template, with possible variations in position and size. The presence of a face was then confirmed by searching for edges at estimated locations of certain features like the eyes and mouth[10-14].

A successful holistic approach to face recognition uses the Karhunen-Loeve transform (KLT). This transform exhibits pattern recognition properties that were largely overlooked initially because of the complexity involved in its computation. But the KLT does not achieve adequate robustness against variations in face orientation, position, and illumination. That is why it is usually accompanied by further processing to improve its performance. An alternative holistic method for face recognition and compares it to the popularly approach. The basic idea is to use the discrete cosine transform (DCT) as a means of feature extraction for later face classification. The DCT is computed for a cropped version of an input image containing a face, and only a small subset of the coefficients is maintained as a feature vector. To improve performance, various normalization techniques are invoked prior to recognition to account for small perturbations in facial geometry and illumination. The main merit of the DCT is its relationship to the KLT. Of the deterministic discrete transforms, the DCT best approaches the KLT. Thus, it is expected that it too will exhibit desirable pattern recognition capabilities[15-21].

A. Transformation Based Systems

Podilchuk and zang proposed a method, which finds the feature vectors using DCT.Their to detect the critical areas of the face. The system is based on matching the image to a map of invariant facial attributes associated with specific areas of the face. This technique is quite robust, since it relies on global operations over a whole region of the face. A codebook of feature vectors or code words is determined for each from the training set. They examine recognition performance based on feature selection, number of features or codebook size and feature dimensionality. For this feature selection, we have several block-based transformations. Among these block-based DCT coefficients produce good low dimensional feature vectors with high recognition performance. The main merit of the DCT is its relationship to the KLT. The KLT is an optimal transform based on various performance criteria. The DCT in face recognition becomes of more value than the KLT because of its computational speed. The KLT is not only more computationally intensive, but it must also be redefined every time the statistics of its input signals change. Therefore, in the context of face recognition, the eigenvectors of the KLT (eigenfaces) should ideally be recomputed every time a new face is added to the training set of known faces[15-21].

B. Karhunen-Loeve Transform

The Karhunen-Loeve Transform (KLT) is a rotation transformation that aligns the data with the eigenvectors, and decor relates the input image data. Here, the transformed image may make evident features not discernable in the original data, or alternatively, possibly preserve the essential information content of the image, for a given application with a reduced number of the transformed dimensions. The KLT develops a new coordinate system in the multi spectral vector space, in which the data can be represented without correlation as defined by:

$$Y = Gx \qquad \ldots (1)$$

Where $\boldsymbol{Y}$ is a new coordinate system, $\boldsymbol{G}$ is a linear transformation of the original Co-ordinates that is the transposed matrix of eigenvector of the pixel data's covariance in $\boldsymbol{x}$ space, and $\boldsymbol{x}$ is an original coordinate system. By the equation for $\boldsymbol{Y}$, we can get the principal components and choose the first principal component from this transformation that seems to be the best representation of the input image.

The KLT, a linear transform, takes the basis functions from the statistics of the signal. The KLT transform has been researched extensively for use in recognition systems because it is an optimal transform in the sense of energy compaction, i.e., it places as much energy as possible in as few coefficients as possible. The KLT is also called Principal Component Analysis (PCA), and is sometimes referred to as the Singular Value Decomposition (SVD) in literature. The transform is generally not separable, and thus the full matrix multiplication must be performed.

C. Quantisation

DCT-based image compression relies on two techniques to reduce the data required to represent the image. The first is quantization of the image's DCT coefficients; the second is entropy coding of the quantized coefficients. Quantization is the process of reducing the number of possible values of a quantity, thereby reducing the number of bits needed to represent it. In lossy image compression the transformation decompose the image into uncorrelated parts projected on orthogonal basis of the transformation. These bases are represented by eigenvectors, which are independent and orthogonal in nature. Taking inverse of the transformed values will result in the retrieval of the actual image data. For compression of the image, the independent characteristic of the transformed coefficients is considered; truncating some of these coefficients will not affect the others. This truncation of the transformed coefficients is actually the lossy process involved in compression and known as quantization. So we can say that DCT is perfectly reconstructing, when all the coefficients are calculated and stored to their full resolution. For high compression, the DCT coefficients are normalized by different scales, according to the quantization matrix [22]. Vector quantization, (VQ) mainly used for reducing or compressing the image data. Application VQ on images for compression started from early 1975by Hilbert mainly for the coding of multispectral Landsat imaginary[15-21].

D. Coding

After the DCT coefficients have been quantized, the DC coefficients are DPCM coded and then they are entropy coded along with the AC coefficients. The quantized AC and DC coefficient values are entropy coded in the same way, but because of the long runs in the AC coefficient, an additional run length process is applied to them to reduce their redundancy. The quantized coefficients are all rearranged in a zigzag order. The run length in this zigzag order is described by a RUN-SIZE symbol. The RUN is a count of how many zeros occurred before the quantized coefficient and the SIZE symbol is used in the same way as it was for the DC coefficients, but on their AC counter parts. The two symbols are combined to form a RUN-SIZE symbol and this symbol is then entropy coded. Additional bits are also transmitted to specify the exact value of the quantized coefficient. A size of zero in the AC coefficient is used to indicate that the rest of the 8 × 8 block is zeros (End of Block or EOB) [1].

Huffman Coding: Huffman coding is an efficient source-coding algorithm for source symbols that are not equally probable. A variable length-encoding algorithm was suggested by Huffman in 1952, based on the source symbol probabilities P (xi), i=1,2… L. The algorithm is optimal in the sense that the average number of bits required to represent the source symbols is a minimum provided the prefix condition is met[15-21]. The steps of Huffman coding algorithm are given below:

- Arrange the source symbols in increasing order of heir probabilities.
- Take the bottom two symbols & tie them together. Add the probabilities of the two symbols & write it on the combined node. Label the two branches with a ‘1’ & a ‘0’
- Treat this sum of probabilities as a new probability associated with a new symbol. Again pick the two smallest probabilities tie them together to form a new probability. Each time we perform the combination of two symbols we reduce the total number of symbols by one. Whenever we tie together two probabilities (nodes) we label the two branches with a ‘0’ & ‘1’.
- Continue the procedure until only one procedure is left (& it should be one if your addition is correct). This completes construction of the Huffman tree.
- To find out the prefix codeword for any symbol, follow the branches from the final node back to the symbol. While tracing back the route read out the labels on the branches. This is the codeword for the symbol.

Huffman Decoding: The Huffman Code is an instantaneous uniquely decodable block code. It is a block code because each source symbol is mapped into a fixed sequence of code symbols. It is instantaneous because each codeword in a string of code symbols can be decoded without referencing succeeding symbols. That is, in any given Huffman code no codeword is a prefix of any other codeword. And it is uniquely decodable because a string of code symbols can be decoded only in one way. Thus any string of Huffman encoded symbols can be decoded by examining the individual symbols of the string in left to right manner. Because we are using an instantaneous uniquely decodable block code, there is no need to insert delimiters between the encoded pixels. For Example consider a 19 bit string

1010000111011011111 which can be decoded uniquely as x1 x3 x2 x4 x1 x1 x7 [7]. A left to right scan of the resulting string reveals that the first valid code word is 1 which is a code symbol for, next valid code is 010 which corresponds to x1, continuing in this manner, we obtain a completely decoded sequence given by x1 x3 x2 x4 x1 x1 x7.

E. Comparison with the KLT

The KLT completely decor relates a signal in the transform domain, minimizes MSE in data compression, contains the most energy (variance) in the fewest number of transform coefficients, and minimizes the total representation entropy of the input sequence All of these properties, particularly the first two, are extremely useful in pattern recognition applications. The computation of the KLT essentially involves the determination of the eigenvectors of a covariance matrix of a set of training sequences (images in the case of face recognition. As for the computational complexity of the DCT and KLT, it is evident from the above overview that the KLT requires significant processing during training, since its basis set is data-dependent. This overhead in computation, albeit occurring in a non-time-critical off-line training process, is alleviated with the DCT. As for online feature extraction, the KLT of an *N* X *N* image can be computed in *O (M_N*2*)* time where *M_* is the number of KLT basis vectors. In comparison, the DCT of the same image can be computed in *O (N*2log2*N)* time because of its relation to the discrete Fourier transform—which can be implemented efficiently using the fast Fourier transform This means that the DCT can be computationally more efficient than the KLT depending on the size of the KLT basis set^2.

It is thus concluded that the discrete cosine transform is very well suited to application in face recognition. Because of the similarity of its basis functions to those of the KLT, the DCT exhibits striking feature extraction and data compression capabilities. In fact, coupled with these, the ease and speed of the computation of the DCT may even favor it over the KLT in face recognition[15-21].

III. SYSTEM STRUCTURE

The process of embedding local appearance-based face representation approach, a detected and normalized face image is divided into blocks of 8x8 pixels size. On each 8x8 pixels block, DCT is performed. The obtained DCT coefficients are ordered using zigzag scanning from the ordered coefficients, according to the feature selection strategy, *M* of them are selected resulting an *M* dimensional local feature vector[15-21]. Finally, the DCT coefficients extracted from each block are concatenated to construct the feature vector. This will be shown in Fig 1 and 2.

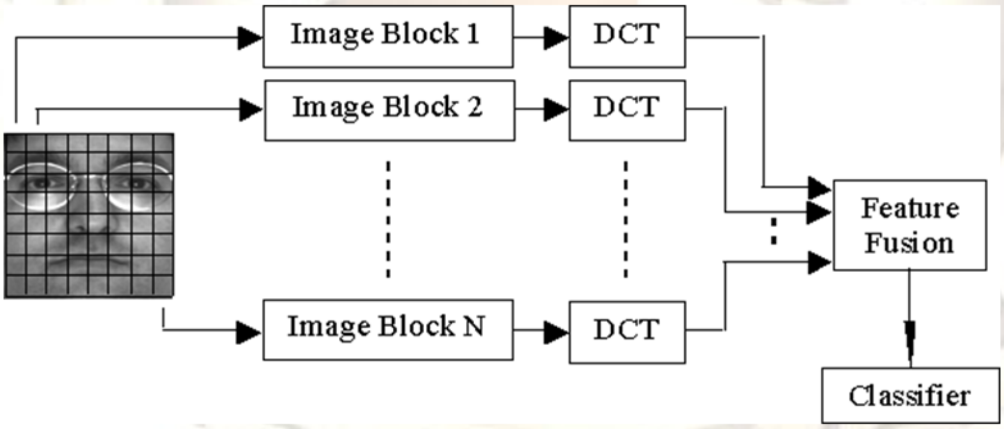

Fig 1 Embedding Local Appearance-Based Face Representation

A. Algorihtm Explanation

The Discrete Cosine Transform (DCT): A DCT expresses a sequence of finitely many data points in terms of a sum of cosine functions. DCT are important to numerous applications in science and engineering. The use of cosine rather than sine functions is critical in these applications for compression, it turns out that cosine functions are much more efficient. In particular, a DCT is a Fourier related transform related to the discrete Fourier transform DFT, but using only real numbers. This type of frequency transform is orthogonal, real, and separable and algorithms for its computation have proved to be computationally efficient. The DCT is a widely used frequency transform because it closely approximates the optimal KLT transform, while not suffering from the drawbacks of applying the KLT. However KLT is constructed from the Eigen values and the corresponding eigenvectors of the data is to be transformed, it is signal dependent and there is no general algorithm for its fast computation. The DCT does not suffer from these drawbacks due to data-independent basis functions and several algorithms for fast implementation. A discrete cosine transform (DCT) is a sinusoidal unitary transform. The DCT has been used in digital signal and image processing and particularly in transform coding systems for data compression/decompression[15-21].

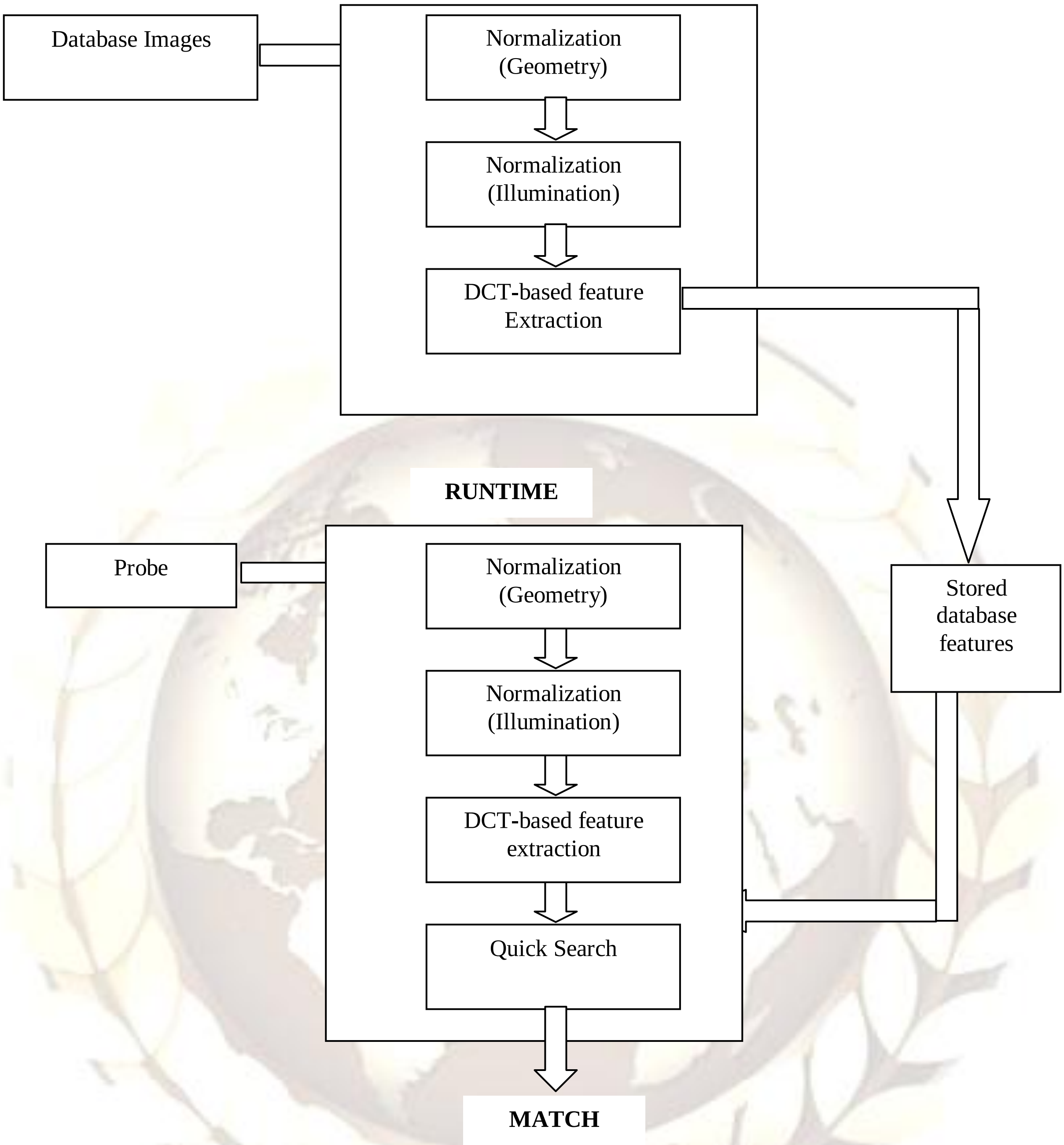

Fig.2 System Architecture

This type of frequency transform is real, orthogonal, and separable, and algorithms for its computation have proved to be computationally efficient. In fact, the DCT has been employed as the main processing tool for data compression/decompression in international image and video coding standards. All present digital signal and image processing applications involve only even types of the DCT. As this is the case, the discussion in this dissertation is restricted to four even types of DCT.In subsequent sections, N is assumed to be an integer power of 2, i.e., $N = 2m$. A Subscript of a matrix denotes its order, while a superscript denotes the version number. Four even types of DCT in the matrix form are defined as

$$\text{DCT} - \text{I}: \quad [C_{N+1}^{I}]_{nk} = \sqrt{\frac{2}{N}}\left[\varepsilon_n \varepsilon_k \cos\frac{\pi nk}{N}\right] \text{ Where n,k=0,1,...N-2}$$

$$\text{DCT} - \text{II}: \quad [C_{N}^{II}]_{nk} = \sqrt{\frac{2}{N}}\left[\varepsilon_k \cos\frac{\pi(2n+1)k}{2N}\right] \text{ Where n,k=0,1,...N-1}$$

$$\text{DCT} - \text{III}: \quad [C_{N}^{III}]_{nk} = \sqrt{\frac{2}{N}}\left[\varepsilon_n \cos\frac{\pi(2n+1)n}{2N}\right] \text{ Where n,k=0,1,...N-1}$$

$$\text{DCT} - \text{IV}: \quad [C_{N}^{IV}]_{nk} = \sqrt{\frac{2}{N}}\left[\cos\frac{\pi(2n+1)(2k+1)}{4N}\right] \text{ Where } \varepsilon_p = \begin{cases} \frac{1}{\sqrt{2}} & p = 0 \; or \; p = N \\ 1 & other\,wise \end{cases}$$

DCT matrices are real and orthogonal. All DCTs are separable transforms; the Multi-dimensional transform can be decomposed into a successive application of one-dimensional transforms (1-D) in the appropriate directions. The DCT is a widely used frequency transform because it closely approximates the optimal KLT transform, while not suffering from the drawbacks of applying the KLT. This close approximation is based upon the asymptotic equivalence of the family of DCTs with respect to KLT for a first-order stationary Markov process, in terms of the transform size and the interelement correlation coefficient. Recall that the KLT is an optimal transform for data compression in a statistical sense because it decorrelates a signal in the transform domain, packs the most information in a few coefficients, and minimizes mean-square error between the reconstructed and original signal compared to any other transform. However, KLT is constructed from the eigen values and the corresponding eigenvectors of a covariance matrix of the data to be transformed it is signal-dependent, and there is no general algorithm for its fast computation[15-21]. The DCT does not suffer from these drawbacks due to data-independent basis functions and several algorithms for fast implementation.

The DCT provides a good trade-off between energy packing ability and computational complexity. The energy packing property of DCT is superior to that of any other unitary transform. This is important because these images transforms pack the most information into the fewest coefficients and yield the smallest reconstruction errors. DCT basis images are image independent as opposed to the optimal KLT, which is data dependent. Another benefit of the DCT, when compared to the other image independent transforms, is that it has been implemented in a single integrated circuit.

The performance of DCTII is closest to the statistically optimal KLT based on a number of performance criteria. Such criteria include energy packing efficiency, variance distribution, rate distortion, residual correlation, and possessing maximum reducible bits Furthermore, a characteristic of the DCT-II is superiority in bandwidth compression (redundancy reduction) of a wide range of signals and by existence of fast algorithms for its implementation. As this is the case, the DCT-II and its inversion, DCT-III, have been employed in the international image/video coding standards: JPEG for compression of still images, MPEG for compression of video including HDTV (High Definition Television), H.261 for compression telephony and teleconferencing, and H.263 for visual communication over telephone lines.

One-dimensional DCT: The one-dimensional DCT-II (1-D DCT) is a technique that converts a spatial Domain waveform into its constituent frequency components as represented by a set of Coefficients. The one-dimensional DCT-III is the processes of reconstructing a set of spatial domain samples are called the Inverse Discrete Cosine Transform (1-D IDCT).The 1-D DCT has most often been used in applying the two-dimensional DCT (2-D DCT), by employing the row-column decomposition, which is also more suitable for hardware implementation.

Two-dimensional DCT: The Discrete Cosine Transform is one of many transforms that takes its input and transforms it into a linear combination of weighted basis functions. These basis functions are commonly in the form of frequency components. The 2-D DCT is computed as a 1-D DCT applied twice, once in the x direction, and again in the y direction. The discrete Cosine transform is of a N x M image $f(x, y)$ is defined by: In computing the 2-D DCT, factoring reduces the problem to applying a series of 1-D DCT computations. The two interchangeable steps in calculating the 2-D DCT are:

- Apply 1-D DCT (vertically) to the columns**.**
- Apply 1-D DCT (horizontally) to result of Step 1.

In most compression schemes such as JPEG and MPEG, typically an 8x8 or 16x16 sub image, or block, of pixels (8x8 is optimum for trade-off between compression efficiency and computational complexity) is used in applying the 2-D DCT. The DCT helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). DCT transforms the input into a linear combination of weighted basis functions. These basis functions are the frequency components of the input data. For most images, much of the signal energy lies at low frequencies these are relocated to the upper-left corner of the DCT. Conversely, the lower-right values of the DCT array represent higher frequencies, and turn out to be smaller in magnitude, especially as u and v approach the sub image width and height, respectively[15-21]. Here we show some approach to basic algorithm

1. Maintain a database with images in JPEG format.
2. Select a Probe for testing.
3. Convert the probe image and database image by apply Normalization Techniques.
4. Process of Normalization
   i. Probe and database images are converted into grayscale images.
   ii. Converted images are resized into 8 X 8 or 16 X 16.
   iii. Feature vector values are derived for the resized images.
   iv. DCT technique is applied to the Feature vector values.
   v. Finally covariance is displayed for both database and probe.
5. Subtract the covariance and feature vector values of probe and database image.

6. If the output value is Zero or negative then the image is recognized. Otherwise image is not recognized

IV. CASE STUDY

Here we study some of the results with different images

Result Objectives: Both Images are same so image is recognized, here we Enter the angle value 0. S = -1.8084e+003

The output is Zero or Negative so object is recognized,

Conclusion: When both the images are in same size but in different angles. If angle is equal then result is pass and image is recognized. Shown in Fig 3

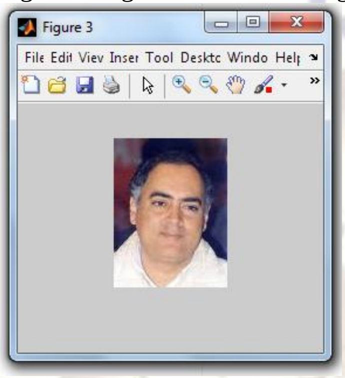

Fig 3 Analysis 1

Result Objectives: Here we taken the same image with equal sizes but they are in different angles. Here we Enter the angle value 8, s = 6.8758e+003, The output is positive so not recognized the object

Conclusion: When both images are in same sizes but in different angles. If Angle is equal then result is pass otherwise fail.so image is not Recognized because Positive value. Shown in Fig 4

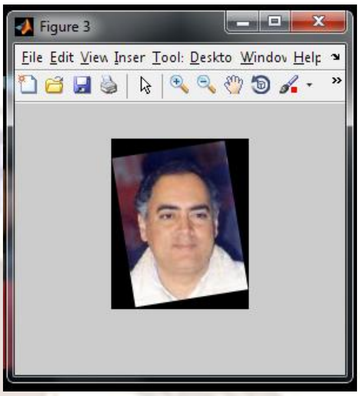

Fig 4 Analysis 2

Result Objectives: Different images are not matched, enter the input image'pic5.jpg', enter the database image'pic1.jpg'

S = 4.8084e+003, The both images are not same,

Conclusion: The input and database images are not same. So they are not matched. Shown in Fig 5

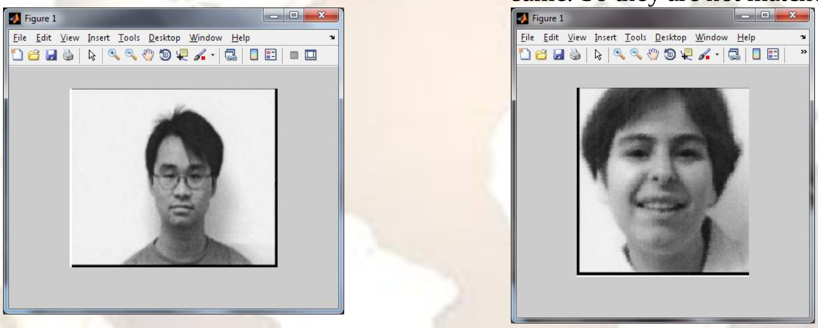

Fig 5 Analysis 3

Result Objectives: Both images are matched. Enter the input image'pic5.jpg', Enter the database image'pic5.jpg', S=0

The output is Zero or Negative so object is recognized, Both Images are same

Conclusion: The input and database images are same. Shown in Fig 6

Fig 6 Analysis 4

V. CONCLUSION AND FUTURE WORK

The Effects Of Feature Selection And Feature Normalization To The Performance Of A Local Appearance Based Face Recognition Scheme. Here, Three Different Feature Sets And Two Normalization Techniques Which Analyze The

Effects Of Distance Metrics On The Performance. This Approach Was Based On The Discrete Cosine Transform, And Experimental Evidence To Confirm Its Usefulness And Robustness Was Presented. The Mathematical Relationship Between The Discrete Cosine Transform (Dct) And The Karhunen-Loeve Transform (Klt) Explains The Near-Optimal Performance Of The Former. Experimentally, The Dct Was Shown To Perform Very Well In Face Recognition, Just Like The Klt. Face Normalization Techniques Were Also Incorporated In The Face Recognition System Discussed Here. It Is Required That A Perfect Alignment Between A Gallery And A Probe Image. We Can Also Extend It To Pose Invariant Face Recognition Method, Centered On Modeling Joint Appearance Of Gallery And Probe Images Across Pose, That Do Not Require The Facial Landmarks To Be Detected .

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