

# Similarity of Inference Face Matching On Angle Oriented Face Recognition

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#### Abstract

Face recognition is one of the wide applications of image processing technique. In this paper complete image of face recognition algorithm is proposed. In the prepared algorithm the local information is extracted using angle oriented discrete cosine transforms and invokes certain normalization techniques. To increase the Reliability of the Face detection process, neighborhood pixel information is incorporated into the proposed method. Discrete Cosine Transform (DCT) are renowned methods are implementing in the field of access control and security are utilizing the feature extraction capabilities. But these algorithms have certain limitations like poor discriminatory power and disability to handle large computational load. The face matching classification for the proposed system is done using various distance measure methods like Euclidean Distance, Manhattan Distance and Cosine Distance methods and the recognition rate were compared for different distance measures. The proposed method has been successfully tested on image database which is acquired under variable illumination and facial expressions. It is observed from the results that use of face matching like various method gives a recognition rate are high while comparing other methods. Also this study analyzes and compares the obtained results from the proposed Angle oriented face recognition with threshold based face detector to show the level of robustness using texture features in the proposed face detector. It was verified that a face recognition based on textual features can lead to an efficient and more reliable face detection method compared with KLT (Karhunen Loeve Transform), a threshold face detector.

**Keywords**: Angle Oriented, Cosine Similarity, Discrete Cosine Transform, Euclidean Distance, Face Matching, Feature Extraction, Face Recognition, Image texture features.

# 1. Introduction

Many authors discussed the face recognition by comparing the face of human being with the database and identifying the features of image. Face Recognition has received considerable attention over past two decades, where variation caused by illumination is most significant factor that alerts the appearance of face Chellappa et al., 1995. The database of system consists of individual facial features along with their geometrical relations. So for the input taken the facial features are compared with the database. If a match is found the face of the person is said to be recognized. In this process we consider feature extraction capabilities of discrete cosine transform (DCT) and invoke certain normalization techniques which increase its robust face recognition.

The face recognition falls in to two main categories, Chellappa et al., 1995; they are (i) feature-based and (ii) holistic. Feature-based approach to face recognition relies on detection and characterization of the individual facial features like eyes, nose and mouth etc, and their geometrical relationships. On the other hand, holistic approach to face recognition involves encoding of the entire facial image. Earlier works on face recognition as discussed by Ziad M.Hafed and Martin Levine 2001, Ting Shan et al 2006, are considered. Alaa Y. Taqa and Hamid A. Jalab 2010 are proposed color-based or texture-based skin detector approaches.

In this paper we discussed a new computational approach that is converting the input image to database image using Angle orientation technique in section2. Section 3 deals with the mathematical definition of the discrete cosine transform its relationship to KLT and Euclidean Distance with Cosine Similarities. The basics of face recognition system using DCT that includes the details of proposed algorithm and discussion of various parameters which affect its performance are discussed in section 4. The experimental results of the proposed

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#### 2. Angle Orientation

First the input image is selected and compared with the database image. If input image size is not equivalent to database size, the input image is to be resized to match with the size of database image. We compare the pose of the image in both input and database images. If the input image is not at an angle of  $90^{\circ}$  we can't compare the images; some authors Ziad. M. Hafed and Martine D. Levine (2001) used eye coordinates techniques to recognize such an image. In this approach one can identify the feature images of the faces even though they are angle oriented. If the input image angle is not  $90^{\circ}$ , rotate the image to  $90^{\circ}$  and then apply normalization technique such as geometric and illumination technique. Recognition of an image by using rotational axis is easy to achieve or recognize the face. When the input image rotates from horizontal axis to vertical axis the face rotates anti-clock wise and the face appears in which it is the same as the database pose, then the object is recognized. Similarly, when the input image rotates from vertical axis to horizontal axis the face rotates clock wise and the face appears in which it is the same as the database pose, then the object is recognized. Therefore if input image is Angle oriented, the pose is changed or Angle is altered using rotational axis and then compared. The Two types of angle rotations, clock wise and Anti-clock wise, with different angles are given in the images of Figure 2.1 and Figure 2.2.



Data Base Image



Input Image



Angle  $\theta = 3$ 



Angle  $\theta = 5$ 

Angle  $\theta = 7$ 



Angle  $\theta = 10$ 



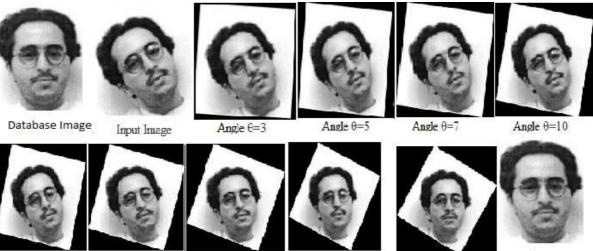




Angle  $\theta = 20$ Data Base Image

Angle  $\theta = 30$ 

Angle  $\theta = 15$ Figure 2.1: Angle Rotation – Anti Clock Wise Direction



Angle  $\theta = 12$ 

Angle  $\theta = 20$ 

Angle  $\theta = 15$ 

Angle  $\theta = 25$ 

Database Image

Figure 2.2: Angle Rotation – Clock Wise Direction



Discrete cosine transform (DCT) has been used as a feature extraction step in various studies on face recognition. Until now, discrete cosine transforms have been performed either in a holistic appearance-based sense [7], or in a local appearance-based sense ignoring the spatial information to some extent during the classification step by feeding some kind of neural networks with local DCT coefficients or by modelling them with some kind of statistical tools.

Ahmed, Natarajan, and Rao (1974) first introduced the discrete cosine transform (DCT) in the early seventies. Ever since, the DCT has grown in popularity, and several variants have been proposed (Rao and Yip, 1990). In particular, the DCT was categorized by Wang (1984) into four slightly different transformations named DCT-I, DCT-II, DCT-III, and DCT-IV. Of the four classes we concern with DCT-II suggested by Wang, in this paper.

y(k, 1) = w(k) 
$$\sum_{n=1}^{N} x(n) \cos \frac{\pi (2n-1)(k-1)}{2N}$$
, k = 1, ..., N (3.0.1)  
Where

$$w(k) = \begin{cases} \frac{1}{\sqrt{N}}, \ k = 1\\ \frac{\sqrt{2}}{N}, \ 2 \le k \le N \end{cases}$$
(3.0.2)

N is the length of x; x and y of the same size. If x is a matrix, DCT transforms its columns. The series is indexed from n = 1 and k = 1 instead of the usual n = 0 and k = 0 because vectors run from 1 to N instead of 0 to N-1.Using the formulae (3.0.1) and (3.0.2) we find the feature vectors of an input sequence using discrete cosine transform.

#### 3.1. Taxonomy of Face Matching Methods

The main objective of matching methods for measure is to define a value that allows the comparison of feature vectors (reduced vectors in discrete cosine transform frameworks). With this measure the identification of a new feature vector will be possible by searching the most similar vector into the database. This is the well-known nearest-neighbor method. One way to define similarity is to use a measure of distance,  $d(\mathbf{x}, \mathbf{y})$ , in which the similarity between vectors,  $S(\mathbf{x}, \mathbf{y})$  is inverse to the distance measure. In the next sub-sections distance measures are shown Euclidean Distance, Manhattan Distance and Cosine similarity.

#### **3.1.0. Manhattan Distance**

Initially, to recognizing a specific input image, the system compares the image's feature vector to feature vectors of the database image using a Manhattan distance which is used shortest distance classifier (Paul E, Black, 1987). If the feature vector of the probe is x and that of a database face is y, where  $x=(x_1, x_2, x_3...x_n)$  and  $y=(y_1, y_2..., y_n)$ . The Manhattan distance,  $d_1$ , between two vectors x, y in an *n*-dimensional real vector space with fixed Cartesian\_coordinate system, is the sum of the lengths of the projections of the line segment between the points onto the coordinate axes.

Manhattan Distance(x, y) = $(x, y) = \sum_{i=0}^{n} |x - y|$ (3.1.0)

#### **3.1.1. Euclidean Distance**:

On the other hand, for recognizing a particular input image, the system compares the image's feature vector to the feature vectors of the database image using a Euclidean distance nearest-neighbor classifier (Duda and Hart, 1973). If the feature vector of the probe is x and that of a database face is y, where  $x=(x_1, x_2, x_3...x_n)$  and  $y=(y_1, y_2...., y_n)$ . The position of a point in a Euclidean n-space is a Euclidean vector. So, x and y are Euclidean vectors, starting from the origin of the space, and their tips indicate two points. The Euclidean norm, or Euclidean length, or magnitude of a vector measures the length of the vector.

Euclidean Distance  $(x, y) = \sqrt{\sum_{i=1}^{n} (x - y)^2}$ (3.1.1) Journal of Information Engineering and Applications ISSN 2224-5758 (print) ISSN 2224-896X (online) Vol 1, No.1, 2011



# 3.1.2. Cosine Similarity

Another face matching distance classifier method where interested is cosine similarity and can be calculated as follows. For any two given vectors x and y, the cosine similarity,  $\theta$ , is represented using a dot product and magnitude as

Cosine Similarity  $(x, y) = (x^T y/||x||.||y||)$ (3.1.2)

For face matching, the attribute vectors x and y are usually the term frequency vectors of the images. The cosine similarity can be seen as a method of normalizing image length during comparison. The resulting similarity ranges from -1 meaning exactly opposite, to 1 meaning exactly the same, with 0 usually indicating independence, and in-between values indicating intermediate similarity or dissimilarity.

# 3.2. Relationship with KLT

Karhunen-Loeve Transform (KLT) is a unitary transform that diagonalizes the covariance or the correlation matrix of a discrete random sequence. Also it is considered as an optimal transform among all discrete transforms based on a number of criteria. It is, however, used infrequently as it is dependent on the statistics of the sequence i.e. when the statistics changes so as the KLT. Because of this signal dependence, generally it has no fast algorithm. Other discrete transforms such as cosine transform (DCT) even though suboptimal; have been extremely popular in video coding. The principal reasons for the heavy usage of DCT are that it is signal independent and it has fast algorithms resulting in efficient implementation. In spite of this, KLT has been used as a bench mark in evaluating the performance of other transforms. Furthermore, DCT closely approximates the compact representation ability of the KLT, which makes it a very useful tool for signal representation both in terms of information packing and in terms of computational complexity due to its data independent nature.

#### 4. Basic Algorithm for Angle Oriented Face Recognition using DCT

The basic algorithm for Angle Oriented Face Recognition discussed in this paper is depicted in figure 3.1. The algorithm involves both face normalization and Recognization. Mathew Turk and Alex Pentland [15] expanded the idea of face recognition. It can be seen in the figure 3.1 that the system receives input image of size N x N and is compared with the size of database image, if the input image and database image are not equal, is to be resized the image. While implementing an image processing solution, the selection of suitable illumination is a crucial element in determining the quality of the captured images and can have a huge effect on the subsequent evaluation of the image. If the pose of the selected image is required to rotate to obtain the database image rotate the face with an angle  $\theta$  until it matches with the database image. The rotation of the image may be bidirectional, clock wise or anti-clock wise, depending on the selected pose of the image.

Once a normalized face obtained, it can be compared with other faces, under the same nominal size, orientation, position, and illumination conditions. This comparison is based on features extracted using DCT. The input images are divided into  $N \times N$  blocks to define the local regions of processing. The  $N \times N$  two-dimensional Discrete Cosine Transform (DCT) is used to transform the data into the frequency domain. Thereafter, statistical operators that calculate various functions of spatial frequency in the block are used to produce a block-level DCT coefficient.

To recognize a particular input image or face, the system compares this image feature vector to the feature vector of database faces using a Euclidean Distance nearest neighbor classifier (Duda and Fart, 1973), Manhattan distance and Cosine Similarity. After obtaining the Manhattan Distance or Euclidean Distances or Cosine Similarity for N x N Matrix one needs to find the averages of the each column of the matrix, and then find the average of all these averages, if the overall average is negative we may say there is a match between the input image and database image.

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#### Input Image

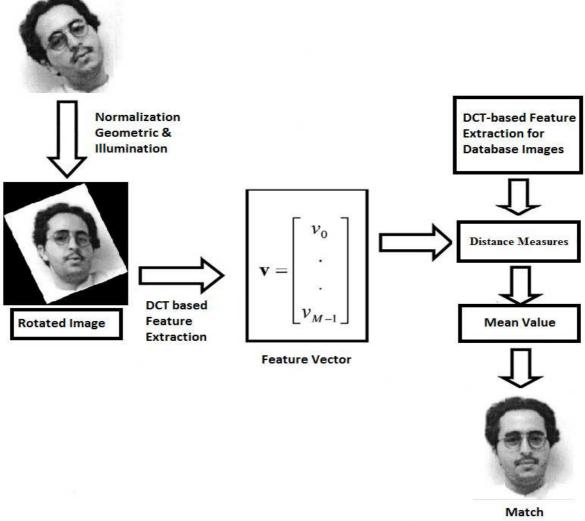


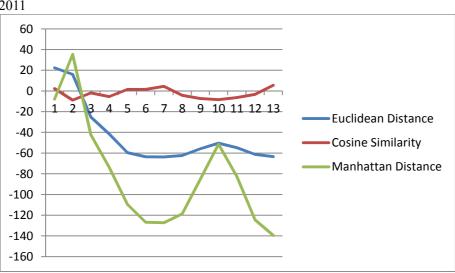
Figure 4.1: Angle Oriented Face Recognition using DCT

#### **5.** Experimental Results

This section is focused on the Discrete Cosine-based face recognition systems using the projection methods and similarity measures previously presented. Two different face image databases were used in order to test the recognition ability of each system image database of the Shree Vasista Educational Society.

#### 5.1. Clock wise Rotation

The experimental Results are calculated for various angles of  $\theta$  in clock wise direction using the three methods Euclidean distance and Cosine Similarity. The mean recognition values of three methods are measured. Out of a sample of 13 observations 12 are recognized. The percentage of recognition for DCT with Manhattan distance is 92.30%.



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Figure 5.1 Mean values for Clock Wise Rotation

The obtained data was presented in Figure 5.1. In Figure 5.1 the red line indicates the recognition level for Cosine Similarity and the blue gives Euclidean distance and green indicates Manhattan distance. It can be observed that the recognition level of input image in DCT with Manhattan distance is very high. It is also noticed that as the sample size is increasing the recognition level is also increasing in DCT with Manhattan distance while comparing with others.

# 5.2. Anti-Clock Wise Rotation

The same methodology as that of clock wise rotation is maintained in anti-clock wise rotation, as well. The comparisons of mean recognition values are Manhattan distance; Euclidean distance and Cosine Similarity for the both methods are calculated for several values of  $\theta$  using Anti-Clock wise direction. In this method also Manhattan distance, Euclidean distance has shown high reliability of recognition level. In Figure 5.2 the results are shown graphically, we can find the rapid decrease in the graph for Manhattan distance, Euclidean distance and Cosine Similarity which showed with blue colored line indicates the high reliability of recognition of the input image.

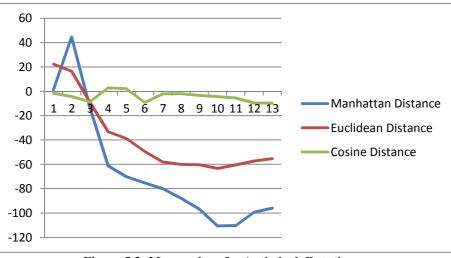


Figure 5.2: Mean values for Anti-clock Rotation

# 5.3. Comparison between DCT and KLT

The DCT and KLT techniques are experimented under standard execution environment by considering the synthesized data of the students of Sri Vishnu Educational Society. The Percentage of recognition level in both the methods of experimental results is shown in Table 4.3.1. The phenomenal growth of DCT reliability is observed when compared with KLT.



The Performance of recognition level of 10000 records for both the methods of experimental results is given in Figure 4.3.2. The graph clearly shows that the reliability performance of DCT is constant increasing with respect to KLT while the number of records is increased.

S. No.	No. of records	Performance in DCT	Performance in KLT
1	1000	91.46	65.42
2	2000	92.01	64.23
3	3000	93.25	52.15
4	4000	94.12	54.12
5	5000	94.62	53.10
6	6000	96.5	52.63
7	7000	97.23	51.71
8	8000	97.56	50.46
9	9000	98.46	50.04
10	10000	98.89	54.13

Table 5.3.1: Performance Records in DCT and KLT

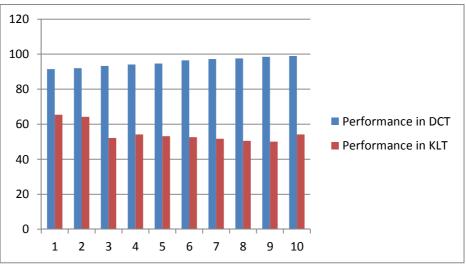


Figure 5.3.2: Bar Chart for Performance in DCT and KLT

# 6. Conclusion and Future Perspectives

Holistic approach to face recognition is used which has involved in encoding the entire facial image. An angle oriented algorithm which can be rotated either clock wise or anti clock wise directions is proposed and successfully implemented through the experimental results. The algorithm is proposed with the mean values of the Euclidian classifiers. It is proved that the proposed angle oriented discrete cosine transform increases the reliability of the face detection when compared with the KLT.

This approach has applications in Intrusion detection and new technologies like Biometric systems etc. The authors view a random variable which indicates the magnitude of the recognition level of an image which will follow some probability distribution.

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