Iris Recognition Using Discrete Cosine Transform and Relational Measures

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Abstract. Iris is one of the most currently used biometric trait as it has random discriminating texture which does not change over a person's lifetime. It is unique for all individuals, even for twins and the left and right eyes of the same individual. This paper describes an iris recognition system which includes phases like segmentation, normalization, segregating unwanted parts like occlusion, specular reflection and noise, enhancement, feature extraction and matching. A new feature extraction technique based on Discrete Cosine Transform (DCT) for iris recognition has been proposed. Also, a new fusion strategy of fusing the dissimilarity scores of the two feature extraction techniques (DCT and Existing Relational Measures) has been proposed to get better performance. The experimental results have been shown on large databases like publicly available CASIA-4.0 Interval and CASIA-4.0 Lamp and self-collected IITK, and the proposed fused approaches have achieved encouraging performance results.

Keywords: DCT, Denoising, CLAHE, Sobel operator, Score-level Fusion

1 Introduction

Personal authentication is a prime social requirement. Biometric based solutions are better than the traditional system of using passwords or identity card for authentication. Most commonly used biometric traits are finger-print, facial features, iris, gait, hand-writing, retina, palm-prints, ear etc. Any biometric traits has to be stable, reliable, universal and unique [12]. The human iris is an annular part lying between pupil and sclera, and has quite irregular characteristics like freckles, furrows, ridges, stripes, etc. These characteristics are unique to each individual, even to different eyes of the same person. Also these textures of iris remain stable during lifetime of an individual. Moreover, it is an internal organ and externally visible, so its image acquisition is almost user-friendly(non-invasiveness).

However, there are some challenges to use iris as biometric trait, like occlusion(hiding of data) due to eyelashes, eyelids and specular reflection and noise, which makes iris recognition inaccurate. An iris feature vector is a binary template which is stored as an attribute and is used to uniquely determine an individual. When an individual uses the biometric system for the first time, the image is enrolled into the system and after some processing it is stored as a template in the database. A typical biometric recognition system can be performed in two modes- verification in which the query image is compared against the template of the individual stored in the database to verify the identity of the person being claimed, and identification in which the query image is matched against all the templates stored in the database to determine the identity of the unknown individual. In the proposed recognition system, first the image is acquired which is then segmented, normalized, denoised and enhanced. The features are extracted using Discrete Cosine Transform (DCT) and Relational Measures (RM). The matching scores of both the approaches are fused using weighted average. Figure 1 shows the flow-chart of the entire proposed iris recognition system.

This paper is organized as follows. Section 2 gives an overview of some of the previous approaches used in iris recognition. Section 3 describes the proposed approach for the recognition system. Experimental results on standard databases are shown in Section 4. Conclusions are given in the last Section.

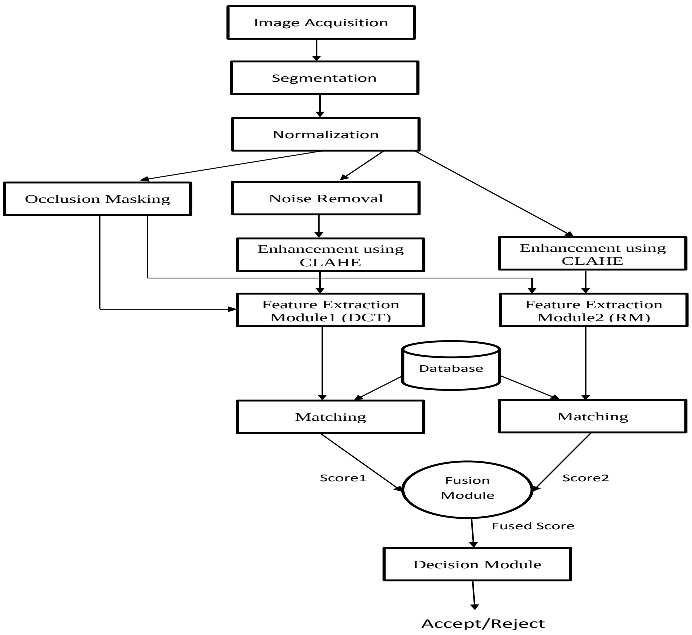


Fig. 1. Overview of the Proposed Iris Recognition System

2 Literature Review

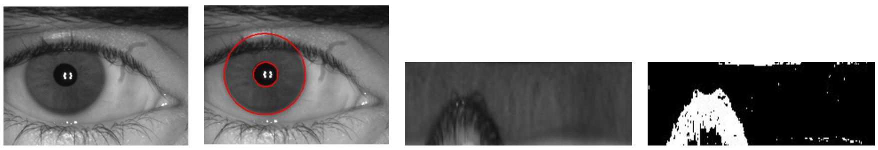
Iris is one of the most efficient and accurate biometric traits. It provides high accuracy and less error rate than other biometric traits like fingerprint and face. Possibly, Flom and Safir [10] are the first one to propose the concept of iris recognition system. Daugman has used the concept of multi-scale Gabor filters to extract iris features [7], [6]. Despite of many advantages of iris, the system should also work over noisy iris images. In [5], [8], Noisy Iris Recognition Integrated Scheme(N-IRIS) has been proposed. Two local feature extraction techniques, i.e., Linear Binary Pattern (LBP) and Binary Large Objects(BLOBs) have been combined to design the scheme. Iris texture is generally irregular distribution of furrows, crypts, ridges, stripes, etc. called blobs. Blobs are generally a group of image pixels forming a structure which is darker or lighter than the surrounding. They are extracted from iris image using different LoG (Laplacian of Gaussian) filter banks which removes noise from the image as well as helps in better detection of blob. This feature extraction approach is invariant to rotation, translation as well as scale. In [9], a new approach of extracting robust iris features using signals like Discrete Wavelet Transform (DWT) and DCT has been proposed. The two-level DWT is applied on the normalized image and then second-level horizontal and vertical detail sub-bands are used. These frequency sub-bands are divided into non-overlapping 8×8 blocks on which DCT is applied. Energies in corresponding DCT-applied blocks are compared which are encoded and used as feature vector template. In [11], [17], the Gabor filter alongwith its response to the image has been discussed. Depending on different spatial frequencies and orientations, Gabor filter can be used effectively for extracting features. Also as the number of Gabor filters for extracting features increases, the more effective discriminative feature vector is extracted. In [14], a new approach of extracting iris features using local frequency variations between adjacent patches of enhanced normalized iris image has been proposed. Overlapping rectangular blocks with some orientation are considered as patches. In this, the patches are averaged widthwise to reduce the noise that gives 1-D signal on which window is applied to reduce spectral leakage and then Fast Fourier Transform (FFT) is applied to obtain spectral coefficients. The differences between the frequency magnitudes of adjacent patches are binarized using zero crossings. This approach gives better performance parameters than other existing state-of-the-art approaches of [6] and [13].

3 Proposed Technique

The iris segmentation is done using the technique proposed in [3]. Iris region is normalized to a fixed size strip so of to deal with iris dilations. One of the major hurdles in iris recognition is occlusion (hiding of iris) due to eyelids, eyelashes, specular reflection and shadows. Occlusion hides the useful iris texture and introduces irrelevant parts like eyelids and eyelashes which are not even an integral part of every iris image.

3.1 Occlusion Detection

Occlusion due to eyelashes, eyelids, specular reflections and shadows hides relevant regions of iris which can severely affect the iris recognition giving inaccurate results. The normalized image is used for finding the occlusion mask to reduce the working area and making detection efficient. Lower and upper eyelids constitute major portion of occlusion in iris image. Based on the property of uniform texture of iris, region growing approach is used for determining eyelids. Region growing [1] is an operation of morphological flood-filling which helps to find objects of almost uniform texture. For region growing algorithm, pixel at last row and column at 1/4th width and pixel at last row and column at 3/4th width of the normalized image for lower eyelid are taken as seed points. There are two types of eyelashes-separable eyelashes, which are like thin threads and multiple eyelashes, which constitute a shadow-like region. Eyelashes have lower intensity value as compared to iris texture. To detect separable eyelashes, standard deviation filter is used and for multiple eyelashes, their low intensity value is given some weightage. Specular reflections are mostly caused due to pixels having very high intensity values. In the normalized image, pixels having intensity value of more than a threshold of 200 are considered as specular reflection. Final occlusion mask is obtained by logical OR-ing all the above three binary masks. The final occlusion mask is shown in Figure 2(d).



(a) Original (b) Segmentation (c) Normalization (d) Occlusion Mask

Fig. 2. Segmentation, Normalization and Occlusion Mask Detection of Iris

3.2 Denoising and Enhancement

Noise in an image results in undesired variation in intensity of pixel values. An average filter of size 4×4 is used for smoothening the image. It is a sliding-window spatial filter which takes the average of all the pixels in the window and assigns it to the central pixel of the window. This helps to remove those pixel values which are quite different from the surrounding. The denoised image is as shown in Figure 3(b). The denoised image may have low contrast and non-uniform illumination. The image is enhanced to make its rich features visible, thereby increasing its discriminative power. For removing noise due to variable illumination conditions, the mean intensity value of each 8×8 block is calculated. Using bicubic interpolation, the resultant 8×8 block is resized, which gives background illumination estimate as shown in Figure 3(c). It is subtracted from the smoothened normalized image with some small weighing factor which gives the uniformly illuminated image as shown in Figure 3(d). The uniformly illuminated image has low contrast, so its contrast is improved using Contrast Limited Adaptive Histogram Equalization (CLAHE) technique [18]. A contrast hiked image is shown in Figure 3(e).

(a) Normalized (b) Denoised (c) Bck. Illu. (d) Uni. Illu. (e) CLAHE

Fig. 3. Denoising and Enhancement

3.3 Feature Extraction

The main aim of iris recognition system is to minimize intra-class differences and to maximize the inter-class differences. But as the iris image is sensitive to various factors like translation, rotation, defocussing, blurring, noise, occlusion, non-uniform illumination, etc., so it cannot be used as a unique iris representation as this may increase the intra-class differences and may also mitigate the inter-class differences. So, a template is generated to represent the iris image in a compact, unique and robust manner. In this paper, two different types of feature extraction techniques are discussed, one uses DCT while other one uses RM [2]. The matching scores of both the techniques are fused by taking weighted average of their scores.

Feature Extraction Using DCT This paper proposes the feature extraction using DCT with some parameters optimized for best performance. A non-conventional technique of applying 1-D DCT on overlapping blocks of particular size for extracting feature variations has been proposed. DCT works well on pixel values lying between -128 to 127 [4], so 128 is subtracted from each pixel value of the enhanced normalized image. This results in a matrix levelled off by 128 from each pixel entry such that all entries in the matrix lie between -128 to 127.

Segmentation into rectangular blocks The levelled-off matrix is divided into rectangular blocks of size $M \times N$ with overlapping of half the width between vertically adjacent blocks and overlapping of half the length between horizontally adjacent blocks as shown in Figure 4(a). These rectangular blocks form the basis of extracting features in our proposed approach. Parameters like length and width of rectangular blocks are tuned to achieve optimum performance.

Coding of Rectangular Blocks The rectangular block is first averaged across its width. This gives a one-dimensional intensity signal of size $1 \times N$. Formally, a rectangular block of width M and length N, averaged across width gives a 1-D intensity signal R' of size $1 \times N$ which can be represented by

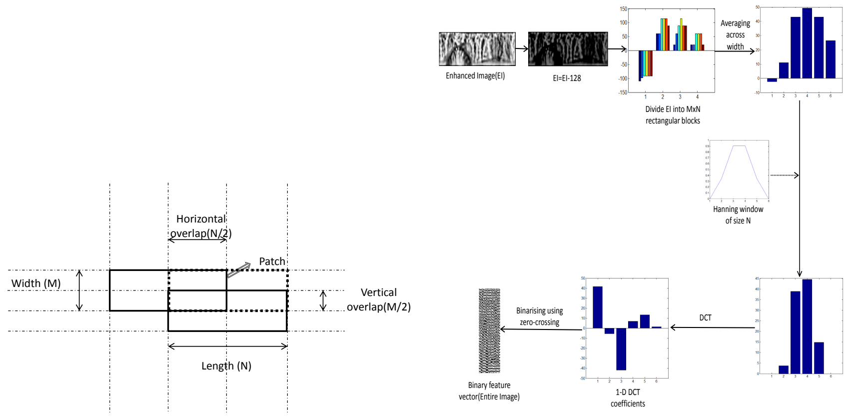
$$R'_j = \sum_{k=1}^{M} R_{j,k} \quad where \;\; j = 1, 2, ..., N \tag{1}$$

Averaging smoothens the image and reduces the effect of noise and other image artifacts [16]. The obtained intensity signal R' is windowed using Hanning window of size N to reduce spectral leakage during the transformation. Application of averaging and windowing also results in reduction of resolution of the image in the horizontal direction. Also image registration becomes easier for broad patches, thereby making iris recognition rotation invariant [15]. 1-D DCT is applied to code the intensity signal which involves low computational cost. The generated 1-D DCT coefficient matrix CM of each rectangular block is binarized using zero crossing to give a binary sub-feature vector B.

$$B_j = \begin{cases} 1 & \text{if } CM_j > 0 \qquad \text{where } j\text{=1, 2, ..., } N \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

A second level occlusion mask based on the feature vector calculation is generated as follows: The corresponding occlusion mask *occmask* is also divided into blocks the same way as the levelled-off matrix. The summation across its width gives a block or patch of size $1 \times N$. If the summation along its width is more than 80% of the width of the block (M), then the bit is masked, i.e., put 1 in the second level occlusion mask; otherwise it is left unmasked or put 0 in the mask. The next bit is then added to the next row and so on. This gives a block of size $N \times 1$. This is done for each overlapping $M \times N$ block in the occlusion mask. Second level mask is required as the feature vector is block-based and not pixel-based. Figure 4(b) illustrates the steps involved in generating feature vector of enhanced normalized iris image. The steps to calculate the feature vector and second level occlusion mask is summarized in Algorithm 1.

Feature Extraction Using Relational Measures In [2], relational measures approach has been used for feature extraction technique. Relational Measures are features which are based on relational operators like $<$, $>$ and $=$. Unlike giving the exact difference between any two quantities, the concept of relational measures is based on finding the relative difference between the two. This encoding into bits is fast and also takes less memory. Also the iris texture has lot of variations in texture; so relational measures concept can be used to encode iris. Vertically and horizontally overlapping regions are chosen from the enhanced normalized image. A central region of size $b \times b$ is chosen. Its four neighboring regions of same size is taken but at a particular distance d, where d is large as compared to b. A symmetric 2-D Gaussian filter centrally clipped to size $b \times b$



(a) Overlapping Rectangular Blocks and parameters

(b) Steps showing the feature vector generation of enhanced normalized iris image (for width M=4, length N=6)

Fig. 4. Feature Extraction using DCT

is put and convoluted over each of these five regions. The response of central region is compared to each of its neighboring regions. If the response of central region is greater than its neighbor, then the bit is encoded as 1, otherwise it is set to 0. In this way, four bits of code are obtained for each central region named as RM bits. This is then iterated for other vertical and horizontal overlapping regions over the entire image. All such RM bits concatenated together gives the 2-D binary template. Second level mask is also generated from the raw occlusion mask of iris based on the feature vector calculation. If the central block has more than 80% of the occluded pixels, then the RM bits for that block are encoded as [1 1 1 1], i.e., masked; otherwise it is encoded as [0 0 0 0], i.e., unmasked. This is repeated for overlapping central blocks according to parameters chosen. This second-level mask is required because the feature vector is block-based and not pixel-based.

3.4 Matching

The feature vector templates and corresponding second level occlusion masks are used in matching. Matching between two iris images takes their respective feature vector templates and second level occlusion masks and calculates the dissimilarity score between the images. The dissimilarity score is calculated using hamming distance metric. Consider two templates t_1 and t_2 of same size, say $X \times Y$ and their second level occlusion masks o_1 and o_2 of same size as that of their feature vector templates, then Hamming distance hd between the templates is calculated using the formula

$$hd(t_1, t_2, o_1, o_2) = \frac{\Sigma_{i=1}^{X} \Sigma_{j=1}^{Y} [t_1(i,j) \ \oplus \ t_2(i,j)] \mid [o_1(i,j) + o_2(i,j)]}{X \times Y - \Sigma_{i=1}^{X} \Sigma_{j=1}^{Y} [o_1(i,j) + o_2(i,j)]} \tag{3}$$

Algorithm 1 $FeatExtract(I, occmask)$

Require: Enhanced Normalized image I of size $Rows \times Cols$, Occlusion Mask $occmask$ of same size as I, M is the width of the rectangular block, N is the length of the rectangular block

Ensure: Feature vector template $Feat$ and Second level occlusion mask $Mask$

$I_{new} \leftarrow$Level off image by subtracting 128 from each pixel value
Initialize a variable $HannFil$ to a Hanning window of size N
$Feat \leftarrow AllocateZero$
$Mask \leftarrow AllocateZero$
Divide I_{new} and $occmask$ into rectangular blocks $B_{i,j}$ and $occBlk_{i,j}$ of size $M \times N$ with overlapping of $M/2$ between vertically adjacent blocks and overlapping of $N/2$ between horizontally adjacent blocks
for each rectangular block $B_{i,j}$ and $occBlk_{i,j}$ **do**
  $MeanBlk_i \leftarrow$ Compute the mean of $B_{i,j}$ across width
  $HannBlk_i \leftarrow$ ElementWiseMultiplication ($HannFil$,Transpose of $MeanBlk_i$)
  $dctBlk_i \leftarrow DCT\ (HannBlk)$ //Extract the 1-D DCT coefficients
  Binarize the 1-D DCT coefficients using zero-crossing to give sub-feature vector f_i
  //Calculating Second level occlusion mask
  $sumarr_i \leftarrow$ Compute the sum of $occBlk_{i,j}$ across width
  for each sum in $sumarr_i$ **do**
    if $sum > 0.8 * M$ **then**
      $resMask \leftarrow 1$ //bit masked
    else
      $resMask \leftarrow 0$ //bit unmasked
    end if
    Concatenate the bits resMask vertically to give a sub-mask $maskBlk_i$
  end for
  Concatenate the sub-features $\{f_i\}$ to give the final feature vector $Feat$
  Concatenate the sub-masks $\{maskBlk_i\}$ to give the final second-level occlusion mask $Mask$
end for
Return $(Feat, Mask)$

where the operators $\oplus$, $|$ and $+$ represent binary XOR, NAND and OR operations respectively. Second level occlusion masks are considered while calculating the dissimilarity score between the two iris images to do matching only in valid bits and not consider the occluded parts of iris images. The value of hd is zero if both feature templates are similar, i.e., have all bits of same value. For genuine matching, hd is low.

Robustness against rotation has also been considered. While acquiring image, there can be some amount of rotation in the image. Rotation of the eye in Cartesian coordinate-space corresponds to horizontal translation in the normalized image. When a probe template is matched with a gallery template, the gallery template is circularly shifted in horizontal direction to get the minimum hamming distance which is taken as the final dissimilarity score. When gallery template is rotated, its corresponding second level mask is also rotated.

4 Experimental Results

The proposed iris recognition system has been tested on two publicly available CASIA-4.0 Interval and CASIA-4.0 Lamp databases and also on IITK database. The iris database is divided into two sets- one is gallery set or the trained set and other one is probe set or query set. Image of the probe set is matched against the image of the gallery set. If the matching is genuine, i.e., the probe image gives the best matching with the correct gallery image then the system is said to correctly recognize that image. In this way, all the probe images are tested and the accuracy of the system is found out by estimating the number of correct recognitions.

4.1 Databases

CASIA-4.0 Interval consists of 2639 images of 249 subjects and each is of size 320×280 pixels taken in two sessions. First three images are taken in the gallery set and rest in the probe set. So total there are 1047 gallery images and 1508 probe images in this database. CASIA-4.0 Lamp Database consists of 16,212 images of 411 people and each is of size 640×480 pixels collected in one session with variable illumination conditions with lamp being switched on/off. Each subject has 20 images. First 10 images per subject have been taken in the gallery set and rest 10 images in the probe set. So total there are 7830 images in both the gallery and the probe sets in this database. IITK Database consists of 20,420 images of 1021 subjects and each is of size 640×480 pixels collected in two sessions in a gap of two days. In each session, 10 images per subject have been collected, with 5 images for each eye. Images in first session are taken in the gallery set and images of second session are considered in the probe set. So total there are 10,210 images in both the gallery and the probe sets in this database.

4.2 Recognition Results using Score-level Fusion of Proposed DCT and RM Approaches

The fusion of matching scores of DCT approach [16] and RM approach [2] is done on the basis of weights determined empirically which gives the best system performance. The weight given to matching scores of DCT approach is more as compared to those of RM approach because the proposed DCT approach gives better system performance as compared to existing RM. Table 1 shows the individual performance parameters of the two approaches as well as the resultant performance parameters of the fused one.

In the proposed DCT approach as well in RM approach, some matchings have been discarded in which the individual mask or the combined mask is more than 85% of the image size. This has been done to avoid inaccuracies caused due to heavy occlusion. Also while fusing the matching scores of the two approaches using weighted average, matchings which are present in both are considered, i.e., the matchings which are present in one and not in other are discarded. So in all, almost 2% of the overall matchings are discarded. On all the databases, CRR

Database	Proposed DCT		RM		Weightage		Fused	
	CRR(%)	EER(%)	CRR(%)	EER(%)	DCT	RM	CRR(%)	EER(%)
Interval	99.40	1.81	99.07	2.26	0.75	0.25	99.40	1.52
Lamp	98.69	3.89	98.69	4.21	0.72	0.28	98.91	2.91
IITK	98.46	2.07	98.66	2.12	0.60	0.40	98.92	1.52

Table 1. Fused Result with weightage given to matching scores of DCT and RM

becomes 100% if top ten matches are considered for identification instead of top one.

4.3 Comparison with Previous Approaches

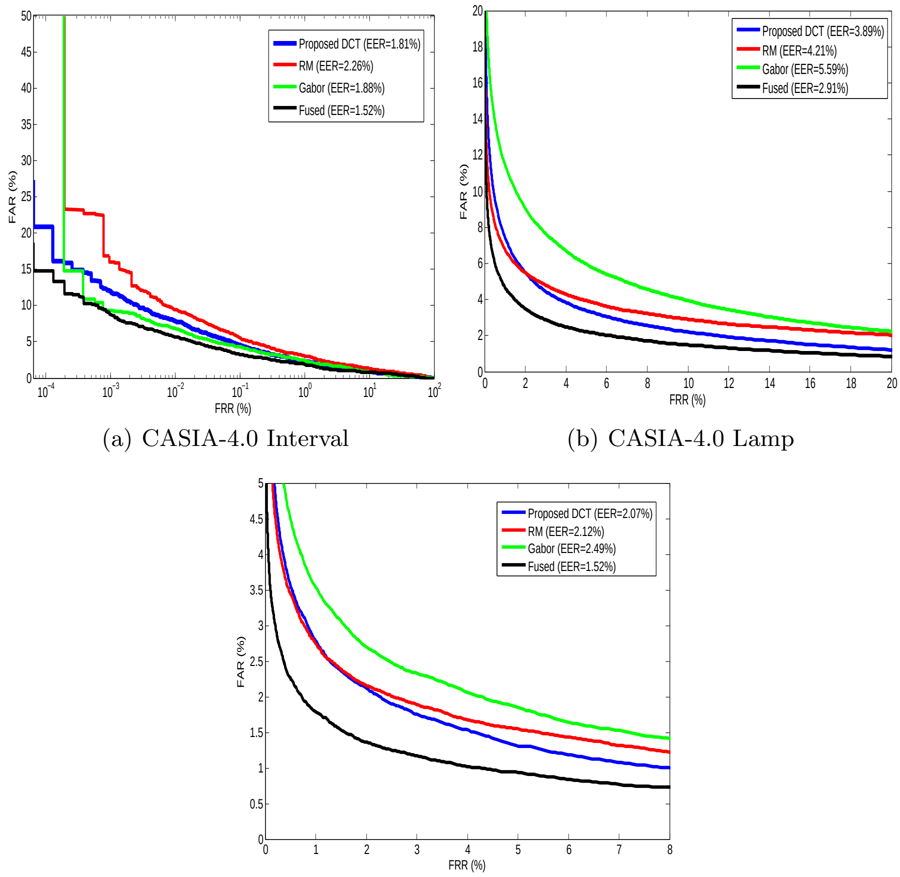
The proposed approach has been compared with that of Daugman$'s$ recognition system [6]. All the pre-processing stages including segmentation, normalization and occlusion masking have been kept common. They differ only in the enhancement and feature extraction phase. The proposed DCT approach uses average filter for smoothing the image as well as non-uniform illumination removal and CLAHE enhancement technique. The Gabor-filtering approach and RM approach use only non-uniform illumination removal and CLAHE for enhancement. The matching scores of both the proposed DCT and RM approaches have been fused using weighted average to get better performance results. All these approaches have been tested on all three databases. Table 2 shows the performance metrics of the four approaches(Gabor-filtering approach, Proposed DCT approach, RM approach and Fused approach of DCT and RM). The ROC graphs of the system on all three databases comparing the four approaches are shown in Figure 5(a), Figure 5(b) and Figure 5(c) respectively. From these figures, it can be seen that the proposed DCT approach has better performance parameters than Gabor-filtering approach and RM approach. The fused approach of DCT and RM has the best performance among all four approaches.

Database	CRR(%)				EER(%)			
	Gabor	RM	Proposed	Fused	Gabor	RM	Proposed	Fused
Interval	99.47	99.07	99.40	99.40	1.88	2.26	1.81	1.52
Lamp	98.90	98.69	98.69	98.91	5.59	4.21	3.89	2.91
IITK	98.85	98.66	98.46	98.92	2.49	2.12	2.07	1.52

Table 2. Comparison of Results on various Databases with different approaches

5 Conclusions

This paper presents an efficient iris recognition system which has been tested on three databases to claim its performance. It has presented the segmentation,



(a) CASIA-4.0 Interval

(b) CASIA-4.0 Lamp

(c) IITK

Fig. 5. ROC Graph based Performance Comparison of all the four approaches

normalization, occlusion mask detection, denoising and enhancement as preprocessing steps. A non-conventional technique based on 1-D DCT has been used to extract robust iris features. Another feature extraction technique of Relational Measures (RM) is based on calculating intensity relationships between local regions and encoding them on the basis of relative difference of intensities. Matching of images is done by using Hamming distance metric based on dissimilarity score. Score-level fusion technique is used to compensate for some images which have been rejected in one approach while accepted in another. This leads to much improved accuracy and less error rate.

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