On Iris Camera Interoperability

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Abstract

With the advancements in iris matching and growing number of system deployments, a wide variety of iris cameras are now being manufactured. These cameras differ in manufacturing technology, including image acquisition spectrum and illumination settings. For large scale applications (e.g. UID system in India) where cameras from several vendors are likely to be used for iris enrollment and authentication, iris camera interoperability is an important consideration. The question we address here is: will the matching accuracy differ in matching iris images captured by two different cameras compared to images captured by the same camera? We propose an iris camera classification-based preprocessing framework to address iris interoperability. The camera classification output is used to perform selective iris image enhancement. Experimental results on the IIITD Multi-Sensor Iris database collected locally and the Notre Dame Cross Sensor database show a significant improvement in the cross-camera iris recognition accuracy using the proposed approach.

1. Introduction

With the emerging large scale deployments of iris recognition [1], iris cameras are now available from different vendors and are based on different technologies. These cameras differ in the range of wavelengths at which they capture irises in the visible and near infrared spectrum, the illumination used during the acquisition process, and other hardware related aspects. Figure 1 shows a set of images of the same eye captured using four different cameras operating at different wavelengths and illumination. Interestingly, these images exhibit large intra-class variations thereby reducing the iris recognition performance. Since iris data is likely to be used for many years after enrollment, the possibility of using different iris cameras for enrollment and identification purposes is rather high. Camera interoperability is therefore an important issue that needs to be addressed for iris recognition systems.

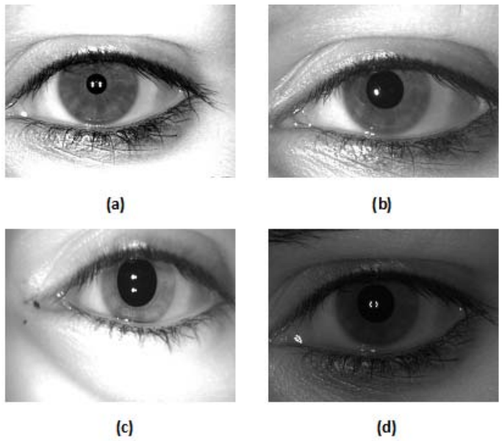

Figure 1. Sample images of the same eye captured using four different iris cameras.

Camera/sensor interoperability has been studied in a wide variety of applications, including fingerprint matching, face, and speaker recognition. Alonso-Fernandez et al. [3] studied sensor interoperability in signature verification using two different tablet PC's and concluded that the verification performance degraded significantly if the enrollment of signatures was done using the sensor with more frequency oscillations. Martin et al. [11] investigated this issue in case of a speaker recognition system and established that using different microphones during enrollment and identification stages reduced the performance considerably. Ross and Nadgir [13] used a thin-plate spine model to address fingerprint sensor interoperability. Bartlow et al. [4], on the other hand, generated noise residual reference patterns for different fingerprint sensors. These patterns were used for identifying the sensor using which the test image was captured. Wavelet based denoising algorithm was then used for achieving sensor interoperability. Alonso-Fernandez et al. [2] used image quality metrics for identifying the sensor in their multi-biometric match score fusion framework.

Bowyer et al. [5] recently investigated this issue in the context of iris biometrics and showed that the genuine and impostor match score distributions from cross-camera iris

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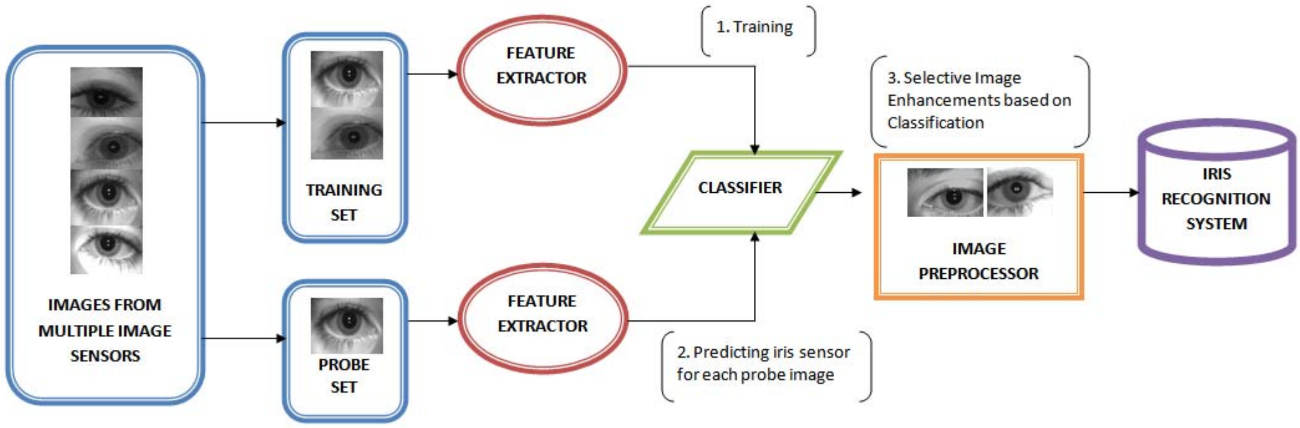

Figure 2. Illustrating the steps involved in the proposed framework for iris camera interoperability.

matching have larger overlap compared to single-sensor iris matching. Connaughton et al. [6] also studied cross-camera iris recognition using two iris cameras and three different matching algorithms. They concluded that there is no clear pattern as to whether single-camera or cross-camera is better and further stated that it was the combination of the algorithm and the camera which determines the overall accuracy of an iris recognition system. Recently, it has been shown in the IREX report [9] that cross camera iris matching results in intermediate performance between the accuracies of lower and upper quality cameras. These contrasting reports have prompted us to investigate this issue further.

In this research, we (a) reinforce that cross-camera iris matching is indeed a challenge for iris recognition systems, and (b) propose a new framework to address this impending issue for improved cross-cameras iris recognition. To support this study, we collected a multi camera iris database, called the IIITD Multi-Sensor Iris (MSI) database containing 208 unique irises of 104 subjects using iris cameras manufactured by two different vendors[1].

2. Iris Camera Classification for Selective Image Enhancement

Iris images acquired using different cameras perceptually differ in contrast, brightness, sharpness, and other image characteristics. These variations, including user habituation, affect the acquired iris image. It is therefore desirable to compensate for this effect while matching iris images acquired using different cameras.

Figure 2 illustrates the steps involved in the proposed framework of iris recognition for iris camera interoperability.

[1]The database can be obtained from http://research.iiitd.edu.in/groups/iab/irisdatabases.html

1. The framework first involves extracting features and learning a classification model for iris camera classification.

2. Using the trained model, the input probe image is classified into one of the iris camera classes.

3. After determining the camera used to capture the iris image, selective enhancement algorithm is applied for every camera model. These enhanced images are then provided as input to the iris recognition algorithms.

2.1. Feature Extraction for Iris Camera Classification

Iris camera classification can be viewed similar to "*source digital camera identification approach*" from the forensic literature [10] in which intrinsic camera properties or image properties are used to identify the source. In this research, two different features have been proposed for iris camera classification: (1) mean and variance based feature vector and (2) Redundant Discrete Wavelet Transform (RDWT) [8] based entropy feature vector.

2.1.1 Feature Set I: Mean and Variance

One of the simplest camera classification approach can be to use mean and variance of the intensity values of the input image. As shown in Figure 3, each iris image from the training set is divided into four quadrants around the iris centre computed using contour based segmentation algorithm [14]. Mean and standard deviation of image intensity values are computed for each quadrant separately and an eight dimensional feature vector is constructed. This feature vector, termed as feature set I, is provided as input to a classifier for training and classification.

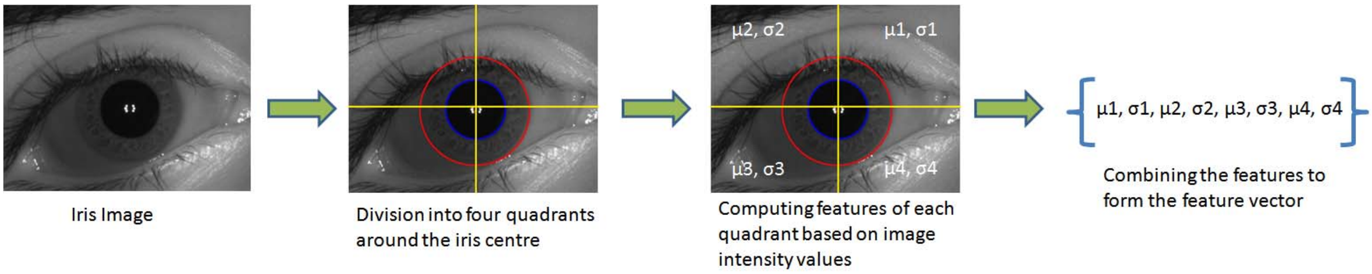

Figure 3. Illustrating the steps involved in extracting feature set I from an iris image.

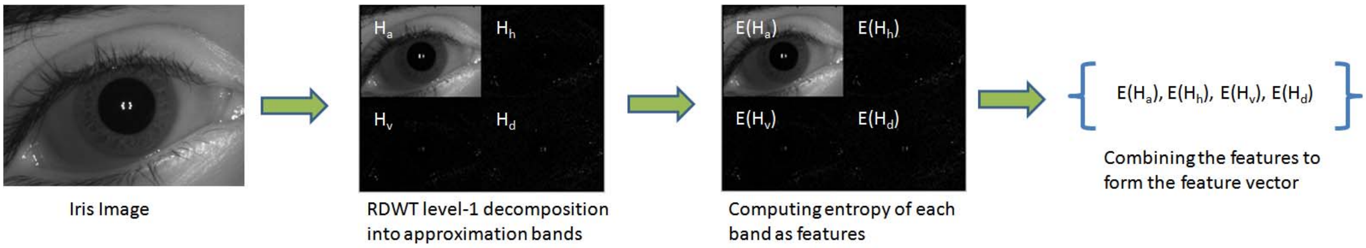

Figure 4. Illustrating the steps involved in extracting feature set II from an iris image.

2.1.2 Feature Set II: RDWT Coefficients

Another approach for camera classification can be to use a combination of spatial and frequency information obtained from the input image. As shown in Figure 4, RDWT decomposed image provides both spatial and frequency information that are used as feature set II for iris camera classification. RDWT provides translation invariance and inherent noise resilience as compared to other transforms such as Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) and has thus been preferred for feature extraction.

Each iris image is first decomposed to obtain wavelet subbands H_a, H_v, H_d, H_h (one approximation and three detailed subbands). The entropy of each subband is then calculated using Equation (1).

$$E(H_i) = \frac{\mu_i - \Sigma H_i(x,y)}{\sigma_i}. \tag{1}$$

Here $E(H_i)$ represents the entropy, μ_i and σ_i are the mean and standard deviation of the RDWT level-1 coefficients of the i^{th} subband respectively and $i = \{a, v, h, d\}$. Thus, a 4-dimensional feature vector, containing the entropy of the four RDWT level-1 subbands is obtained and termed as feature set II.

2.2. Iris Camera Classification

Let $S = \{S_1, S_2, S_3, ..., S_n\}$ denote the set of n different iris cameras and $I = \{I_1, I_2, I_3, ..., I_m\}$ be the set of m images captured using any $S_i \in S$. The first step involves establishing the one-to-one correspondence $I_j \leftrightarrow S_i, \forall I_j \in I$. In other words, given an image $I_j \in I$, its mapping to the source iris camera $S_i \in S$ needs to be ascertained. For classification, certain discriminative features of the images pertaining to different iris cameras are extracted such as feature set I or II. Let these p features be represented by feature vector $\theta = \{\theta_1, \theta_2, \theta_3, ...\theta_p\}$. For learning the classifier, the *training set* comprises a subset of t images from the image set I with known correspondences $I_j \leftrightarrow S_i$:

$$I_{train} = \{I_1, I_2, I_3, ..., I_t\} \tag{2}$$
$$\exists\{I_j \leftrightarrow S_i\}, \forall I_j \in I_{train}, S_i \in S$$

The feature vector θ for each of the t training samples is then computed to obtain the *feature vector set*, Θ_{fs}.

$$\Theta_{fs} = \{\theta(I_1), \theta(I_2), \theta(I_3), ..., \theta(I_t)\}; \forall I_j \in I_{train}. \tag{3}$$

The feature vector set, Θ_{fs}, is then used to train a n-class classifier C (in this case 2-class linear SVM) to map an iris image with the associated iris cameras using which it is captured.

2.3. Selective Image Enhancement

Let $A = \{A_1, A_2, A_3, ..., A_l\}$ be the set of l different image enhancement algorithms. Our objective is to select one or more of these image enhancement algorithms for each iris camera. This essentially involves finding one-to-many mapping $S_i \rightarrow A_q$, where $A_q \in A$; $\forall S_i \in S$.

Let the set of enhancements corresponding to each iris camera S_i be represented as π_i so that we have a one-to-one correspondence $S_i \leftrightarrow \pi_i$ and $\pi_i \in \pi$. Given a probe image with unknown correspondence $I_j \leftrightarrow S_i$, let $I_j \in I$ be represented as I_{probe} and θ_{pr} be its feature vector. The trained classifier C is used for mapping the probe image I_{probe} with iris camera $S_{classified}$.

$$\begin{aligned} S_{classified} = \{S_i\} \\ \exists\{C(\theta(I_{probe})) \rightarrow S_i\}, \exists S_i \in S \end{aligned} \quad (4)$$

Based on the classification result, an enhancement algorithm is selected for the probe image.

In this research, two iris image enhancement algorithms are proposed (one for each camera). The *background* Bg of the image is first calculated using the morphological operation of image opening with a square structuring element:

$$Bg(I_i) = Open(I_i) \quad (5)$$

This is followed by the application of different linear intensity transformations for probe images corresponding to the two cameras considered here:

$$\begin{aligned} I_i &= I_i \ominus c1 * Bg(I_i) \quad if \quad S_{classified} = S_1 \\ &= I_i \oplus c2 * Bg(I_i) \quad if \quad S_{classified} = S_2 \end{aligned} \quad (6)$$

where $\ominus$ and $\oplus$ are mathematical operations and depends on the image properties. Additionally, the images captured using iris camera S_1 also show a significant amount of motion blur. Therefore, an additional step of Wiener filter based deblurring is applied:

$$I_i = Wiener(I_i) \qquad if \;\; S_{classified} = S_1 \quad (7)$$

Finally, image enhancement algorithm π_i is applied to the probe image based on the classified source camera, $S_{classified}$, to obtain the *preprocessed* probe image $I_{pre-probe}$:

$$\begin{aligned} I_{pre-probe} = \{\pi_i(I_i)\} \\ \exists\{S_{classified} \leftrightarrow \pi_i\}, S_{classified} \in S, \pi_i \in \pi. \end{aligned} \quad (8)$$

The preprocessed image $I_{pre-probe}$ is then used for cross-camera iris matching. Note that similar preprocessing can be done on the training set I_{train} with known correspondences directly for iris interoperability. The probe image is thus preprocessed before being used in cross-camera iris recognition experiments.

3. Database

In this research, we have used two databases to evaluate the performance of the proposed framework: Notre Dame Cross Sensor Iris Database[2] and IIITD Multi-Sensor Iris Database prepared by the authors.

[2]http://cse.nd.edu/ cvrl/CVRL/Data_Sets.html

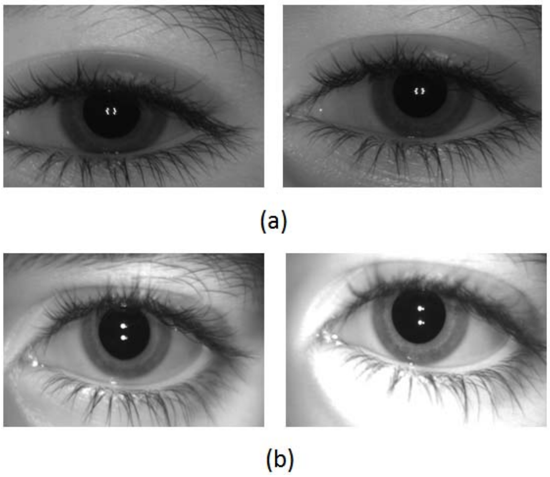

Figure 5. Sample images from the IIITD Multi-Sensor iris database (a) captured using a single eye camera and (b) captured using a dual eye camera.

3.1. Notre Dame Cross Sensor Iris Database

Notre Dame database is the first publicly available database for cross-camera iris matching. The database is prepared using two LG iris camera models: LG2200 and LG4000. The database comprises 264,945 iris images of 676 unique subjects captured in over 27 sessions. In this research, we have evaluated the performance of the proposed algorithms on Set 1 of the ND database which consists of images from 176 iris classes.

Though there are design differences between these two LG cameras, we believe that the interoperability inferences made on this database cannot be generalized to other scenarios containing iris cameras from two different vendors. The authors therefore prepared a new iris database using two different iris cameras (by different vendors).

3.2. IIITD Multi-Sensor Iris Database

In this Multi Camera Iris database, iris images pertaining to 104 subjects (age group of 10-70 years, 55% males and 45% females), are captured using two iris cameras: the first camera is a high end dual eye camera from L1 and the second camera is a low cost single eye camera from Vista. Two images of each eye are captured using both the cameras. In this process, room temperature, lighting and other factors were kept essentially the same so that the image variations, could primarily be attributed to the iris cameras. Under the assumption that iris patterns of the two eyes of a person are independent [7], the database contains 208 unique iris classes. Since each iris has been captured twice (in the same session), we have 416 images per camera, resulting in a total of 832 images from both the cameras. Figure 5 shows sample iris images from the IIITD MSI database.

4. Results and Analysis

For experiments, two commercial iris recognition systems are used and they are termed as commercial-of-the-shelf system 1 (COTS1) and commercial-of-the-shelf system 2 (COTS2)[3]. The following subsections show the results of the proposed camera classification and selective enhancement algorithms on the two databases.

4.1. Results of Camera Classification

The proposed cross-camera iris matching framework is evaluated by dividing the database into 40% training and 60% testing. Therefore, for the MSI database, out of a total of 208 iris classes, 83 classes are randomly selected for training and the remaining 125 are used for testing. Similarly, on the Notre Dame database, images pertaining to 70 irises are used for training and the remaining are used for testing. On each database two linear SVM classifiers are trained using the two feature sets. The classification accuracies of the two classifiers are then computed on the probe set with five times random cross-validation.

Table 1 summarizes the result of this experiment on the IIITD MSI and Notre Dame databases with feature set I and II respectively. The results show that RDWT based features (feature set II) yield higher camera classification accuracy compared to the simplistic mean and variance vector (feature set I), specially on the Notre Dame database. One of the reasons of lower performance by feature set I is its dependence on iris center computation. Incorrect iris localization leads to incorrect feature localization and hence lower classification accuracy. Further, the Notre Dame database has several images where only partial (cropped) iris patterns (in some cases - no iris pattern) are available. On the other hand, feature set II is independent of iris localization and encodes both spatial and frequency information for better classification. As mentioned previously, RDWT also provides resilience to artifacts such as noise, thereby providing additional advantage over feature set I. We further observe that the results of both the classifiers are highly correlated and therefore no benefit can be achieved in combining these features.

4.2. Iris Recognition with Camera Interoperability

To evaluate the performance of iris recognition algorithms for single camera and cross-camera matching, the following three experiments are performed:

1. the matching accuracy is computed when both gallery and probe iris images are captured using camera S_1,
2. the matching accuracy is computed when both gallery and probe iris images are captured using camera S_2,
3. the matching accuracy is computed when gallery images are captured using camera S_1 and the probe images are captured using camera S_2.

[3]The names of both the COTS cannot be revealed due to the restrictions in the license agreements. However, both of them are among the top performing algorithms in the recent IREX report.

Database	**Feature**	**Accuracy (Mean $\pm$ SD)** (%)
MSI	Feature set I	98.30 ± 0.15
MSI	Feature set II	99.68 ± 0.0008
Notre Dame	Feature set I	82.36 ± 0.0032
Notre Dame	Feature set II	92.39 ± 0.0007

Table 1. Iris camera classification accuracies on the two databases. The accuracy is computed over five random splits of the data.

Database	**Image Enhancement**	**COTS1** (%)	**COTS2** (%)
MCI	No enhancement	91.6	94.0
	Intensity Correction	92.4	94.8
	Wiener Deblurring	93.6	94.8
	Proposed - Feature Set I	95.0	95.6
	Proposed - Feature Set II	96.8	96.1
Notre Dame	No enhancement	96.3	96.5
	Intensity Correction	96.9	97.1
	Wiener Deblurring	97.1	97.4
	Proposed - Feature Set II	97.9	98.5

Table 2. Iris verification accuracies, at 0.01% FAR, of the two commercial systems for different enhancement techniques. The results are computed with cross-camera images on both the MCI and Notre Dame databases.

For each probe image, classification result is obtained from the classifier and selective enhancements are then applied to iris images according to Equations (4) to (6). For the MSI database, in Equation (4), $\ominus$ and $\oplus$ are the difference and sum operators respectively and the parameters $c1$ = 0.65 and $c2$ = 0.25. The performance of the proposed framework is compared with enhancement algorithms applied on the complete probe set irrespective of camera classification and the matching results are shown in Figures 7 and 8 and Table 2.

- At 0.01% False Accept Rate (FAR), COTS1 yields the verification accuracy of 96.2% for single-camera matching using S_1 and 99.8% for single-camera matching using the iris camera S_2. On the complete database with cross-camera matching, COTS1 provides an accuracy of 91.6%. These results are obtained without using the proposed selective image enhancement. Similarly, COTS2 yields 97.4% verification accuracy using iris camera S_1, 99.8% for iris camera S_2, and 94.0% for cross camera matching.
- The proposed algorithm yields significant accuracy improvement for cross-camera matching for both COTS1 and COTS2 matchers as shown in Table 2 and Figures 7 and 8. A comparative analysis with existing enhancement techniques indicates that the proposed algorithm yields better overall recognition results using

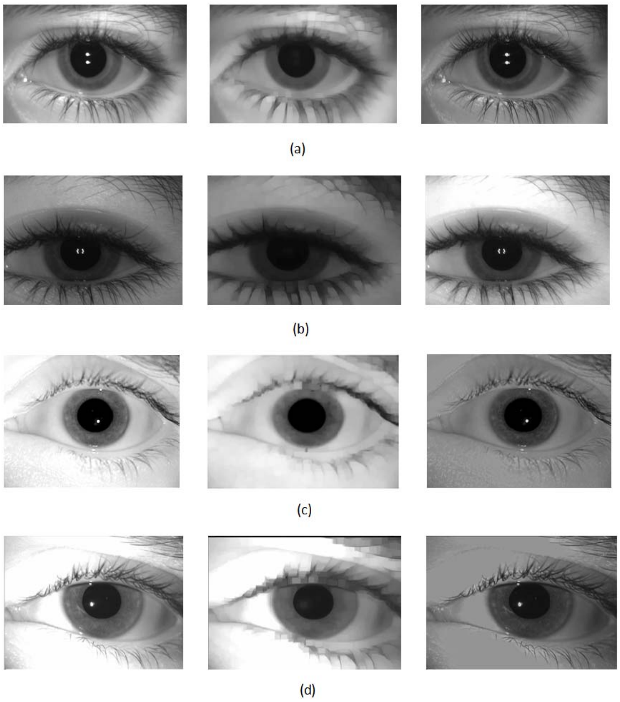

Figure 6. Results of the proposed selective enhancement algorithm on (a) and (b) IIITD MSI database and (c) and (d) Notre Dame database. The first column represents the original input image, the second column represents the background image, and the third contains the the enhanced image.

both feature sets I and II. Using feature set I, the Genuine Accept Rate (GAR) for COTS1 increases by at least 3.5%. Similarly, the GAR for COTS2 shows an increase of at least 1.5% when using feature set I. On the other hand, GAR for COTS1 improves by at least 5% and by 2% for COTS2 when using feature set II.

- We also performed the same set of experiments on the Notre Dame Cross Sensor Iris database. As mentioned previously, similar to the MSI database, this database has images captured using two iris cameras by the same vendor. ROC curves in Figure 9 show that for both the COTS, LG4000 iris camera yields better accuracies compared to LG2200. Further, Figure 10 shows that with cross camera matching the accuracy drops by at least 0.5%. Though this decrease in accuracy is minor but considering that both the cameras are from the same vendor and this variation is caused due to technological advancements (i.e., LG 4000 is an advanced version of LG 2200 camera), this is still significant. Figure 9 shows that on pre-processing the images using the proposed algorithm (with feature set II),[4] the accuracy of cross camera iris matching is up to 98.5%.

[4]Since feature set I provides very low camera classification accuracy on the Notre Dame database, we performed the preprocessing using selective enhancement techniques with feature set II only.

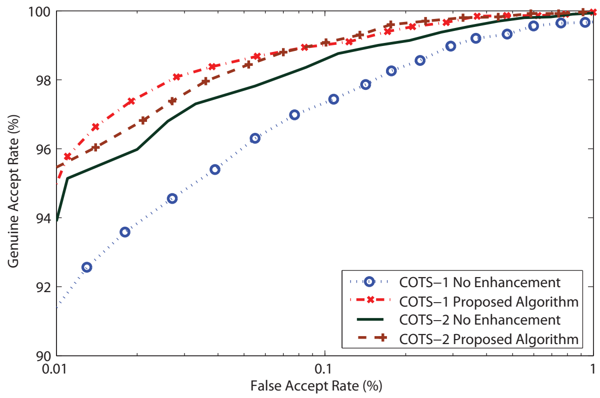

Figure 7. ROC curves illustrating the performance of the proposed algorithm using feature set I for cross-camera matching using COTS1 and COTS2 matchers on the IIITD MSI database.

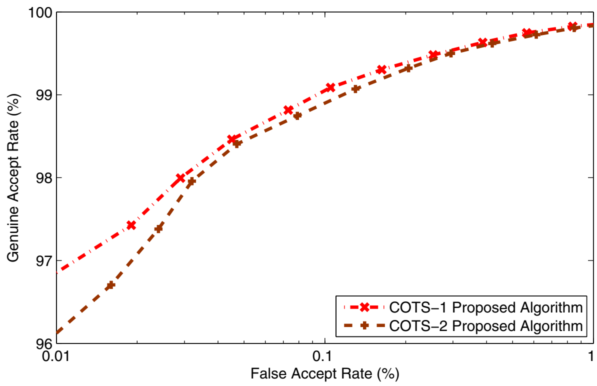

Figure 8. ROC curves showing the effect of the proposed RDWT feature based camera classification and selective enhancement on the iris recognition performance of both the COTS. These cross-camera matching plots are shown on the IIITD MSI database.

- It is observed that the images misclassified (i.e. incorrect verification) after applying the proposed enhancement algorithm are a proper subset of the misclassifications obtained without applying the selective enhancement for cross camera matching. This implies that the proposed algorithm does not introduce any error in iris matching, it has only improved cross camera iris verification.

5. Conclusion

This research addresses the problem of cross-camera iris recognition with different types of iris cameras and matching algorithms. We proposed a framework that first predicts the source camera for every input iris image and then applies selective image enhancement algorithms to minimize the difference between the two iris images captured

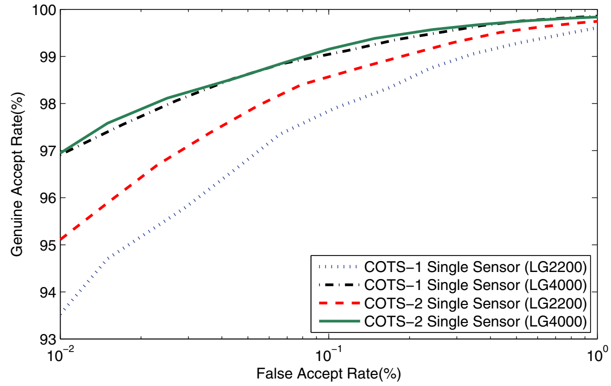

Figure 9. ROC curves illustrating the performance of COTS1 and COTS2 matchers for single camera scenarios on the Notre Dame database. It is to be noted that these results are of direct matching and the camera classification and enhancement algorithms have not been applied here.

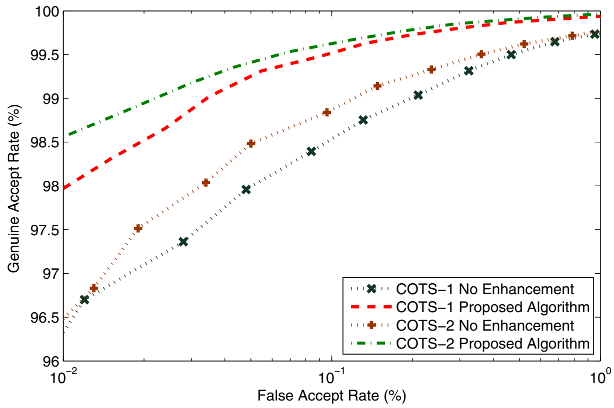

Figure 10. ROC curves showing the effect of the proposed RDWT feature based camera classification and selective enhancement on the iris recognition performance of both the COTS. These cross-camera matching plots are shown on the Notre Dame database.

using two different cameras. The performance of the proposed algorithm is evaluated on the IIITD Multi Camera Iris database and Notre Dame Cross Sensor Iris database. The experimental results show that the proposed framework of camera classification and selective iris image enhancement algorithm improves the cross-camera matching accuracy.

6. Acknowledgement

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