A New Encoding of Iris Images Employing Eight Quantization Levels

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***Abstract*—Biometric systems provide automatic identification of the people base on their own characteristic features. Unlike the other biometric systems such as face, voice, vein, fingerprint recognitions, iris has randomly scattered features. Iris recognition is considered as the one of the most reliable and accurate biometric identification system. It consists of four stages such as; image acquisition, image preprocessing, image feature extraction, and image matching process. In this work, we are proposing a new feature extraction method and new matching metric in order to find an effective threshold value to separate the intra and inter class distribution of the iris images of different people by using eight – level quantization. Instead of using whole iris region, we have used statistically pre-selected iris regions. This selection had reduced the computational time and decreased the storage capacity. Our suggested metrics is rotation invariant and compares two vectors' selected rows calculated by the Fourier Transform. We have suggested eight level quantization of the phase information in order to create iris feature extraction. Finally, we have shown ROC Curves to check the accuracy of our proposed metric. The accuracy of our work is 99.0%, proposed threshold value is 0.746 where FAR is 0.07%, FRR is 39.32% and AUC is 0.97. Using the CASIA Iris Database, we have compared our proposed matching metric with Hamming Distance metric and we report better performance in terms of matching time.**

***Index Terms*—pattern recognition, iris recognition, feature vector extraction, biometrics, roc curves, quantization**

I. Introduction

Iris is the annular part between the pupil and the white sclera, has a complex pattern. This pattern is unique and stable for people's whole life. Iris recognition is considered as the one of the most reliable and accurate biometric identification system. Uniqueness and stability make iris recognition systems a particularly favorable solution for security.

Iris recognition system usually has four main stages such as; Iris image acquisition, Image Pre-processing, Feature vector extraction and template creation, and matching. A complete and detailed explanation of the steps followed in iris recognition was given for the first time in the patent application of Daugman [1]. An image may be analyzed based on the pixel intensity information or on the phase information. As the illumination may be different in different realistic situations, the phase information is more essential in iris recognition. The phase information in its most essential interpretation carries the repetition patterns of the pixel intensities across the image. The Fourier transform helps extract this important information. The Fourier transform of an image can be taken: (i) over rows or columns (one-dimensional) or (ii) over the whole image (two-dimensional). More detailed information on the phase information is found using short window Fourier transforms or as it called Gabor transform. By the help of the Gabor transform, can be determined the frequencies of the pixel intensity 'islands' across the whole iris image [2]. Once the phase information is identified, it is assigned values that facilitate the construction of a metric that would then enable the measurement of the similarity score between any two iris images.

Research has focused on these stages by developing and optimizing algorithms that are tested on well-known iris databases. The first approach has been to modify the already established techniques. All of the main stages have been improved including the detection of the inner and outer iris boundaries and the improvement of the handling of the statistical inference methods [3]. Ma *et al*. analyzed key local variations in the iris intensity and employing wavelets they reported positive results [4]. Here, in this work, we have modified the way that the templates are created from the phase information and introduce a new metric to compare them.

II. Stages of Iris Recognition

A. Iris Image Acquisition

Image acquisition is the first step of iris recognition process. Since every person has different size and color of iris, image acquisition step is being very complex process. Capturing clear iris images is very difficult with the standard CCD cameras in different circumstances. Generally, iris image acquisition distance is 2 feet to 3 feet in one or two seconds. Sometimes the acquisition step yields different results for the same person because of the different lighting effects, or not keeping the capturing distance [5].

The size of the diameter of the iris is approximately 11 mm and its color is varying base on the nationalities of the people. Image acquisition plays a critical role in iris recognition due to the best matching performance directly

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proportional to images that have been taken good. Poor imaging implies high unlikeness for the intra-class comparisons [6]. In contrast, inter class scores are independent of image quality [7].

B. Image Pre-Processing

Iris pre-processing includes the localization, segmentation and normalization stages. These are very important for recognition success rate. Iris localization determined the inner and outer boundaries of the iris region in order to use in the feature analyzing process. Localization can be considered the one of the most difficult part in the iris identification system [8]. Segmentation aims to accurately localize iris boundaries without noise (eyelids, eyelashes, reflection, occlusion). Normalization aims to get a rectangular iris texture by mapping the annular iris information between pupillary and limbic boundaries of the iris region that is firstly has been proposed by John Daugman by using polar coordinates [9].

Mistakes in the segmentation process cannot be recovered at the other stages. Masking in the step is also very important. Segmentation problems indicate false rejections.

There are different segmentation methods, such as edge points detection and curve fitting, [10] but mainly the ones that are used are the Integro–differential operator and Hough Transform [11].

C. Feature Vector Extraction

Feature vector extraction aims to generate an optimum representation of characteristic of the iris texture code in order to get best performance for the matching step. The generated features are registered to the system database.

Binary and real valued representations are used for the feature extraction till now. John Daugman has used binary feature vectors in his iris code and it supports the matching process by quantizing intermediate features. J. Daugman's iris code algorithm used 2D Gabor wavelets. The 2D Gabor function is defined as

$$G(x,y) = e^{-\pi\left((x-x_0)^2\alpha^2+(y-y_0)^2\beta^2\right)}.e^{-2\pi i\left(u_0(x-x_0)+v_0(y-y_0)\right)} \quad (1)$$

where β/α is the aspect ratio of the Gaussians, x_0/y_0 is the center in the spatial domain and u_0/v_0 specify harmonic modulation with special frequency $\sqrt{u_0^{\,2}+v_0^{\,2}}$ and orientation $\arctan(x_0/y_0)$. Phase information has been used and quantized by using two bits encoding the phase quadrant. The most widely accepted way of identifying the phase information is the assignment of the phase of each pixel according to the quadrant where it belongs. The whole phase space is quantized in four levels. The four quadrants are assigned values of "11", "01", "00", "10" for the first, second, third and fourth quadrant, respectively [12]. These values assigned constitute the template of an iris and these templates are used to compare different eyes. The choice of these values has been done in a relatively clever way that matches very well with the statistical method that is used to quantify the similarity between the irises. Statistically speaking, when one uses a XOR operator, there is a 50% difference between any subsequent quadrant and a 100% difference between any two opposite quadrants.

D. Matching

While comparing feature vectors, we get the similarity score of the biometric characteristics of two iris images. Using Hamming Distance (HD) metrics [13] has been compared two feature vectors. Range of the HD is through '0' to '1'. If HD is 0, then compared images are same; basically we are comparing an iris with itself. On the other hand, if HD is 1, compared images are completely different. A threshold value has to be found, such that the results that are below or equal to the threshold value will be considered the same images, and the results that are above the threshold value be considered different images. The threshold value may be slightly different from one database to another. Earlier works on CASIA database have used a threshold value HD = 0.4. Now, recently J. Daugman has used HD = 0.33 [13]. So comparison results that are less than or equal to 0.33 indicate that the images are from the same person, otherwise the irises are from different peoples.

$$HD = \frac{\left\|(code\,A \otimes code\,B) \cap mask\,A \cap mask\,B\right\|}{\left\|mask\,A \cap mask\,B\right\|} \quad (2)$$

There are two types of matching such that verification and identification. Verification is one-to-one comparison, whereas the identification is one to all comparison. Two iris images of the same person would ideally have a hamming distance equal to zero (highest similarity score). Two iris images from different persons would have a hamming distance equal to one (lowest similarity score). Practically this is as impossible as having a correlation coefficient of zero or a correlation coefficient of one: even for randomly generated data. (One would find a hamming distance equal to zero only when comparing an iris image with itself.) So instead of obtaining hamming distances of zero and one, we find distributions represented by a histogram with HD values in the lower range as seen in Fig. 1 and another histogram with HD values in the higher range as shown in Fig. 2. Figures throughout 1 to 3 are obtained using only the images that we have selected to test the algorithm that we have developed in this. In developing a metric to measure the similarity score among iris images, the main objective is to obtain two completely non-overlapping histograms as shown in Fig. 3. Once we have an overlap between these two histograms, one has to define a threshold value that aims to assign an equal error in rejecting the same person and in accepting a different person.

Numerous metrics have been used to get the performance of the iris recognition and hamming distance is one of them. The parameters that are reported or indicate the performance of a metric are: False Acceptance Rate (FAR) or False Positive (FP), False Rejection Rate (FRR) or False Negatives (FN) and Equal Error Rate (EER), Genius Acceptance Rate or True

Positive (TP) is 1 – FRR [14]. If FAR, FRR, and EER are all 0, then genius and imposter images are perfectly separated. Generally, FAR and FRR results are inversely proportional. When working with a database to test the algorithms that are developed, the number of the interclass dual comparisons is at least two orders more than the number of intra-class dual comparisons. This fact that is shown in Fig. 4 (not to scale), automatically introduces some difficulties in the analysis of the algorithms. When FAR and FRR are equal to zero then this means that we have a perfectly working biometric system and as a result the EER is also zero. The first difficulty is that the histograms that we like to be non-overlapping do in fact overlap.

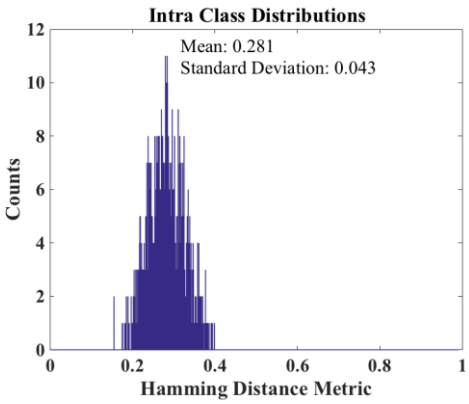

Figure 1. Intra - Class hamming distance distributions

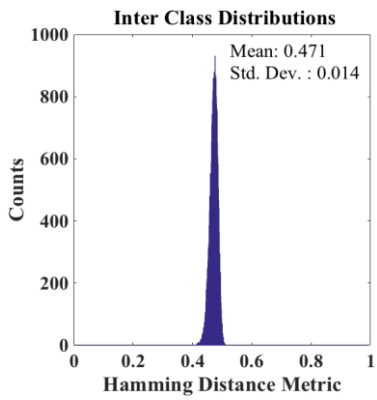

Figure 2. Inter - Class hamming distance distributions

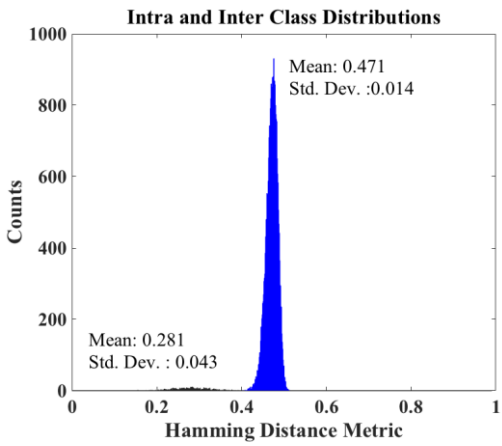

Figure 3. Intra & inter class hamming distance overlap

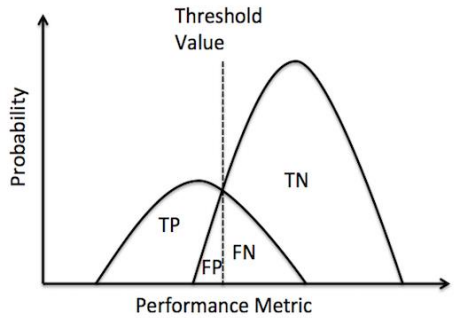

Figure 4. Performance metric parameters

The next difficulty is that the overlapping histograms are not of the same order. Another parameter that is used to control the efficiency of the biometric system is the accuracy. Achieving a high accuracy means a maximization of the sum of TP+TN, or otherwise a minimization of the FP+FN. When calculating the accuracy, the TN has a higher weight than the TP, since the interclass dual comparisons are at least two orders more. When calculating the EER there is no weight of the two factors (FAR and FRR) considered. This means that the accuracy and the EER are never simultaneously at their optimal value for the same threshold value. This creates a situation where ambiguous results are reported.

To visualize biometric system errors and the efficient threshold value, we generally use Receiver Operating Characteristics (ROC) curves [15].

III. Proposed Method

Our recommended method reconsiders the encoding step and the matching step. In the encoding step we have used the Daugman's algorithms and we have increased the quantization level to eight and have denoted the eight quantization levels of the phase space using '1', '2', '3', '4', '5', '6', '7', '8' as shown in Fig. 5 instead of '11', '01', '00', '10' as seen in Fig. 6 that are used when dividing the phase space in four levels.

In order to get this quantization level, complex coordinate plane has been divided into eight equal parts that can be seen in Fig. 5 and corresponding iris feature data function has been registered to the our template's corresponding row and column position.

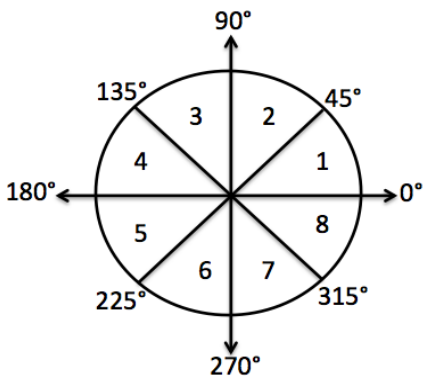

Figure 5. Encoding by 8 level quantization method

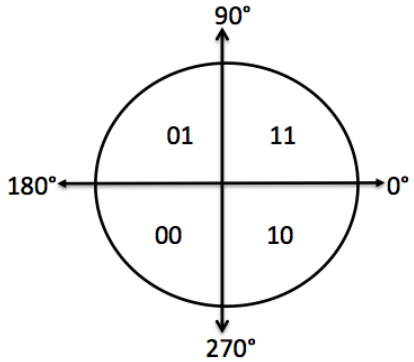

Figure 6. Encoding by 4 level quantization method

HD template has a size of 20 by 480. Having small size of a template indicates less storage place and better performance in terms of computational time during the matching process. Later on, for the matching metric we have used only nine rows of the created iris template that we have obtained, from the second to tenth row. We have selected these specific rows after doing several tests that proved that they give the best matching performance. In our proposed matching metric we have used the rotational invariant one-dimensional Fourier Transform (1D - FFT). This metric is rotation invariant that lifts the necessity of the shifting of the templates during the matching process and considers it as redundant. Our metric value is defined as:

$$\frac{1}{4500}\sum_{i=1}^{9} norm\left(abs\left(fft\left(u_i\right)\right)-abs\left(fft\left(v_i\right)\right)\right) \qquad (3)$$

We have used 35 people's best-segmented eye images from CASIA-1 database [16], i.e. from a total of 108 people. Every eye image has 7 different iris images of the same person. In order to test the algorithms, we made up a smaller set of iris images that included only the persons whose 21 possible dual comparisons among the 7 images reported a score below the threshold value, thus confirming that it is the same person. The results of the intra-class comparison do not show the precise result because of the CASIA database has mostly the images that have characteristic real-life defects such as eyelids block the iris, or the eyelashes cover the iris as seen in Fig. 7.

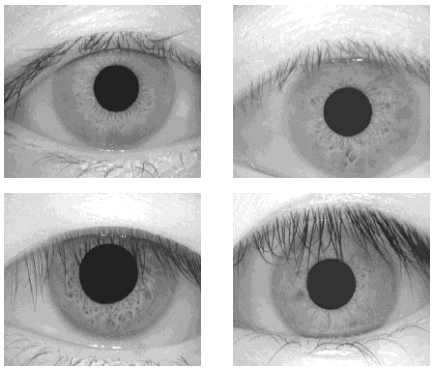

Figure 7. Sample of iris images from CASIA database

Two iris images of the same person would ideally have a Fourier Transformation (FT) metric equal to zero (highest similarity score). Two iris images from different persons would have a FT metric equal to one (lowest similarity score). Practically this is as impossible as having a correlation coefficient of zero or a correlation coefficient of one: even for randomly generated data. (One would find a FT metric equal to zero only when comparing an iris image with itself.) So instead of obtaining FT metrics of zero and one, we find distributions represented by a histogram with FT values in the lower range as seen in Fig. 8 and another histogram with FT values in the higher range as shown in Fig. 9.

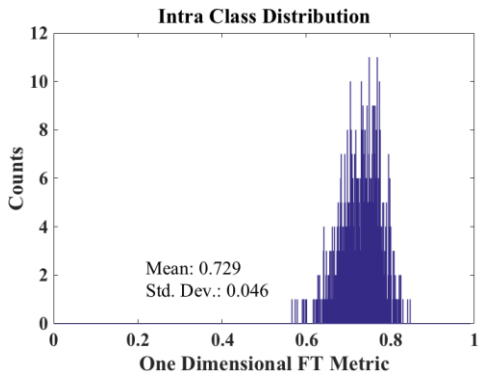

Figure 8. Intra - Class 1D Fourier transformation distribution

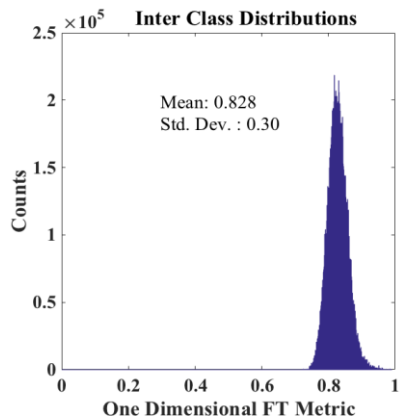

Figure 9. Inter - Class 1D Fourier transformation distribution

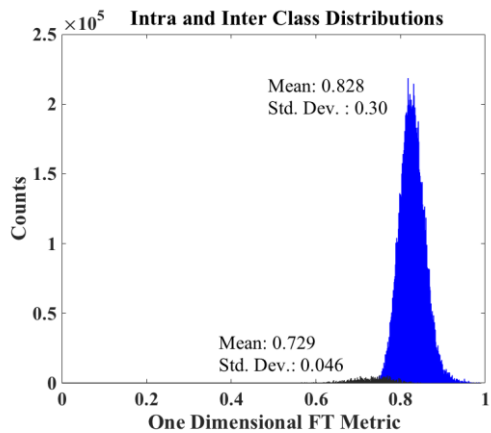

Figure 10. Intra & inter class 1D Fourier transformation overlap

Figures throughout 8 to 10 are obtained using only the 245 images that we have selected to test the algorithm that we have developed in this paper as shown in Ref. [6].

In developing a metric to measure the similarity score among iris images, the main objective is to obtain two completely non-overlapping histograms as shown in Fig. 10. Once we have an overlap between these two histograms, one has to define a threshold value that aims to assign an equal error in rejecting the same person and in accepting a different person.

Besides these mentioned problems, the CASIA database is a good set to work with and test the algorithms.

IV. Results

After sketching the ROC curves, by utilizing the Area Under the ROC curve, we have decided to choose the optimum threshold value as 0.746 where the accuracy value is 99.0%, area under curve is 97.4% and d-prime test result is 3.5. In deciding the threshold value, the optimization of the accuracy was our main objective. For this reason, as explained also in sections above, the other parameter that is used to measure the performance of the algorithm, the EER is not optimal. The EER that we find using the new metric is 39.3%. Reports of relatively high values of EER have been common in literature alongside the negative connotation that it bears [17]. The ROC curve is shown in Fig. 11 and shows the dependence of True Positive Rates vs. False Positive Rates while the threshold value changes from 0 to 1. When comparing our result with the J. Daugman's Hamming Distance method, we get good results since the Hamming Distance metric reports an accuracy of 99.7% and the one dimensional Fourier Transform that we propose with the eight level quantization reports an accuracy of 99.0%. We have tabulated computational time performance of the our metric and Hamming Distance metric by using the same people's different iris images in Table I and different people's different irises in Table II.

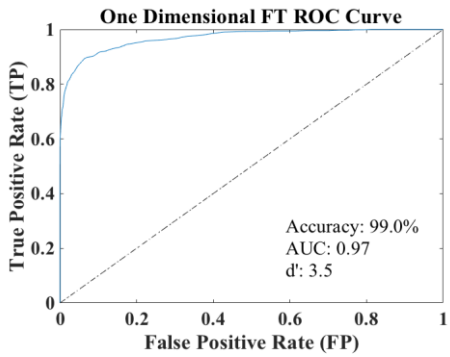

Figure 11. ROC curve of 1D FFT metric

TABLE I. Running Time Performance of HD and 1D FFT Metrics for Iris Recognition

	HD Average Running time	FFT Average Running Time
Same Image Comparisons	8.53 seconds	8.38 seconds

TABLE II. Running Time Performance of HD and 1D FFT Metrics for Iris Recognition

	HD Average Running time	FFT Average Running Time
Different Image Comparisons	10.49 seconds	10.50 seconds

The results for the accuracy and the EER of the new metric have been compared with the results obtained using the hamming distance for the best-segmented 245 iris images. We will test our Fourier Transform metric again for the whole images of the CASIA database and will compare again how the accuracy will change.

V. Conclusion and Future Work

Most of the biometric systems use the J. Daugman's iris recognition algorithm. We have used a different matching metric after increasing the number of quantization level from four to eight. The new matching metric gives an accuracy of 99% as seen in Fig. 11 and shows better performance in terms of running time as seen in Table I. We have used some mathematical functions such as; mean, Euclidian norm, absolute value, and Fast Fourier Transformation. Our metric is defined in (3) normalized mean of two feature vectors' rows through second to tenth, which gives us the best accuracy result in the selected iris region. From the results shown as in Table I and Table II we observe that the newly introduced metric gives satisfactory results. With the new metric, there is no need for the shifting of the two templates during the comparison, as it is rotation invariant. Another reason for high accuracy has to do with the fact that we use the rows that are closer to the pupil and the angular resolution of 240 corresponds to approximately to 1-1.5 pixel per degree.

A better optimization can be achieved if we modify the similarity score that uses the 1D - FT by conducting a more detailed statistical analysis rather than using the average value in order to decrease the overlap region as shown in Fig. 10 between intra-class and inter-class region which increases the overall accuracy of the biometric system.

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