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Iris Recognition Using Gaussian Pyramid Compression and Modified Distance Measures

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Abstract

Iris recognition is one of important biometric recognition approach in a human identification is becoming very active topic in research and practical application. In this paper, Gaussian pyramid compression technique is used to compress the eye image and this compressed eye is used for the localization of the inner and outer boundaries of the iris region. Located iris is extracted from the compressed eye image and after normalization and enhancement it is represented by a data set. With Gaussian pyramid compression improved matching performance is observed down to 0.25 bits/pixel (bpp), attributed to noise reduction without a significant loss of texture. To ensure that, the iris-matching algorithms are not degraded by image compression. Hamming distance, Modified Normalized Euclidean Distance and Modified Average Euclidean Distance methods are evaluated using MMU iris image database [8] and achieved high accuracy. Experimental results demonstrate that the proposed methods can be used for human identification in an efficient manner.

Keywords: Iris recognition, Biometric, Gaussian, 1D-Log Gabor filter, Hamming Distance.

Introduction

A Biometric system is a pattern recognition system that determines the authenticity of an individual using some physical or behavior features. The requirement for reliable personal identification in computerized access control has resulted in an increased interest in biometrics. Current systems employ many different biometric traits, including fingerprints, iris images, face images, retinal scans, palm prints and gait patterns. Biometrics based on the iris is among the most accurate existing techniques for human identification and verification. No two iris patterns are alike, even those of identical twins, even between the right and left eye of the same person [2]. The human iris is not changeable and is stable. From one year of age until death, the patterns of the iris are relatively constant over a person's life-time [2, 3]. Because of this uniqueness and stability iris recognition is a reliable human identification technique.

With the growing employment of iris recognition systems and associated research to support this, the need for large databases of iris images is growing. If required storage space is not adequate for these images, compression [15] is an alternative. It allows a reduction in the space needed to store these iris images, although it may be at a cost in some amount of information lost in the process. There are many loss-less compression algorithms available that work best on certain types of data, such as predictive coding for one dimensional data and string coding for text.

Among the various loss-less compression algorithms available today, achievable compression is of the order of 1.5:1 to 3:1. Alternatively, lossy codes can compress images further with varying degrees of loss. Pyramid compressions have demonstrated very good loss-less compression performance with most types of imaginery [14]. This consists of a set of low-pass or band-pass copies of an image, representing pattern information of a different scale.

In this paper, we investigate that the effect of pyramid compression on the ability of an iris recognition system to accurately identify individuals. Typically a database for an iris recognition system does not contain actual iris images, but rather it contains the compressed iris images. The performance is evaluated by means of the change in the Hamming distances between Iris codes using an iris recognition implementation based on several algorithms including Libor Masek's algorithm [9]. We seek to compress the original imagery because it is the data that is valuable and serves as training and testing imagery for the development of new algorithms. Typically a database for an iris recognition system does not contain actual iris images, but rather it stores the compressed images stored as 512 bytes per eye. Compression has been investigated and used in some biometric applications such as the FBI standard for fingerprint compression [7][8] using MPEG compression [9]-[10] for video that may be used in facial recognition applications. There have been some limited research in the area of iris image compression [10] but this was compression applied to Iris Codes, not iris images. Here, Gaussian pyramid compression is applied to the iris imagery itself.

This paper is organized as follows. In Section 2, the iris preprocessing steps that include detailed introduction to iris compression, localization, normalization and enhancement are described; and also provide feature extraction. Section 3 discusses iris matching based on hamming distance. Experiments and results are reported in Section 4. Conclusion is drawn in Section 5.

Iris recognition

The overall system structure of the iris recognition includes image acquisition and iris recognition. The iris image acquisition includes the lighting system; the positioning system and the physical capture system. The iris recognition includes preprocessing and iris template matching.

Image Preprocessing

Standard noise reduction and isolated peak noise removal techniques such as median-filtering and average filtering used to clear the noise and to make the iris textures good and clear. In practical applications of a workable system an image of the eye to be analyzed must be acquired first in digital form suitable for analysis. Here we have used the MMU iris image database available in the public domain. In this stage, we transformed the images from RGB to gray level for further processing. Before extracting features from the original image, the image needs to be preprocessed to localize iris, normalize iris and reduce the influence of the factors such as brightness, non-uniform illumination, etc., such preprocessing is described in the following subsections.

Gaussian Pyramid compression

The original image is convolved with a Gaussian kernel. The resulting image is a low-pass filtered version of the original image.

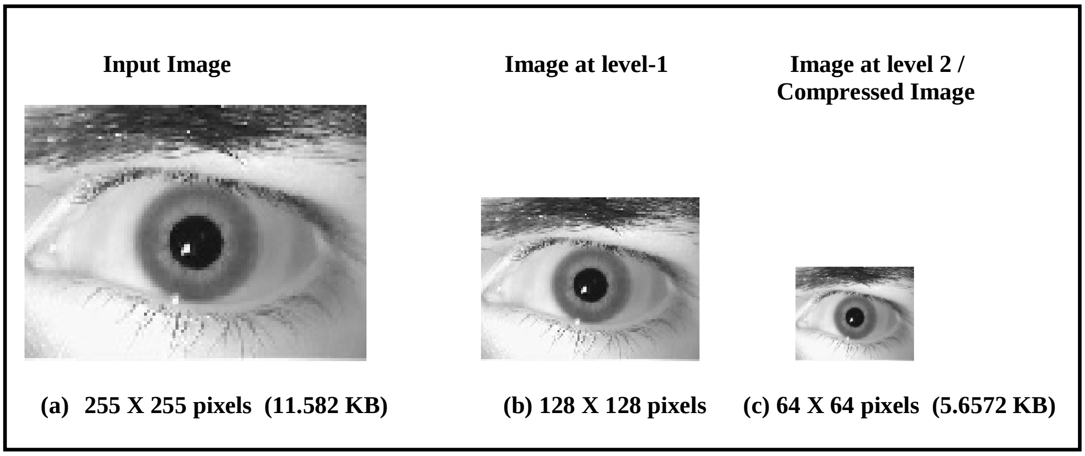

Figure 1: Low pass filter effect of the Gaussian pyramid, which is of the order of 1.7:1 for RGB image and 1.9:1 for gray image.

The original image, level 0 measures 255 by 255 pixels and each higher-level array is roughly half the dimension of its predecessor. Thus, level 2 measures just 64 by 64 pixels. We have selected the 2-by-2 patterns because it provides adequate filtering at low computational cost. The low-pass filter effect of the Gaussian pyramid, which is of the order of 1.7:1 for RGB image and 1.9:1 for gray image, is clearly shown in the Figure 1.

Iris localization

Before performing iris pattern matching, the image is compressed by Gaussian pyramid, and then the boundaries of the iris are to be located. In other words we are supposed to detect the part of the image that extends from inside the limbus (the border between the sclera and the iris) to the outside of the pupil. Integro-differential operator is used for locating the inner and outer boundaries of iris as well as the upper and lower eyelids [4]. The operator computes the partial derivative of the average intensity of circle points with respect to increasing radius *r*. After convolving the operator with Gaussian kernel, the maximum difference between inner and outer circle will define the center and radius of the iris boundary. For upper and lower eyelids detection, the path of contour integration is modified from circular to parabolic curve. The operator is accurate because it searches over the image domain for the global maximum. It can compute faster because it uses the first derivative information.

Iris Normalization

Irises from different people may be captured in different size and even for the iris from the same person; the size may change because of the variation of the illumination and other factors. Such elastic deformations in iris texture affect the results of iris matching. For the purpose of achieving more accurate recognition results, the homogenous rubber sheet model devised by Daugman [1] used to remap each point within the iris region to a pair of polar co-ordinates (r, θ) where r is on the interval [0,1] and θ is the angle $[0,2\pi]$.

The remapping of the iris region I(x, y) from raw co-ordinates (x, y) to the doubly dimensionless non concentric polar co-ordinate system (r, θ) can be represented as

$$(I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta)$$

With $x(r, \theta) = (1-r)\, x_p(\theta) + r x_1(\theta)$

$$y(r, \theta) = (1-r)\, y_p(\theta) + r y_1(\theta)$$

Where I(x, y) is the iris region image (x, y) are the original Cartesian co-ordinates, (r, θ) are the corresponding normalized polar co-ordinates and x_p, y_p and x_1, y_1 are the co-ordinates of the pupil and iris boundaries along the θ direction. The rubber sheet model takes into account pupil dilation and size inconsistencies in order to produce a normalized representation with constant dimensions.

Iris Enhancement

The normalized iris image has low contrast and non-uniform illumination caused by the light source position. The image needs to be enhanced to compensate for these factors. Local histogram analysis is applied to the normalized iris image to reduce the effect of non-uniform illumination and obtain well-distributed texture image [11][12]. Reflections regions are characterized by high intensity values close to 255. A simple thresholding operation can be used to remove the reflection noise.

Feature Extraction

In order to extract the discriminating features from the normalized collarette region, the normalized pattern is convolved with 1D Gabor wavelets [9]. Thus, feature encoding is implemented by first breaking the two-dimensional normalized iris pattern into one-dimensional wavelets and then these signals are convolved with 1D Gabor wavelet. The resulting phase information for both the real and imaginery response is quantized, generating a bit wise template. In this work, the angular and radial resolutions are set as 240 and 20 pixels, respectively. Two bits are used to represent the quantized phase information for each pixel. Therefore, the total size of the iris template is 9600 bits.

Template Matching

The final step in iris identification stage is to determine whether two irises belong to same class by viewing the similarity of their feature vectors. Three types of measures such as Hamming Distance [2], Modified Normalized Euclidean Distance [9] and Modified Average Euclidean Distance [16] are used for classification.

A. Hamming Distance

This test enables the comparison of two iris patterns. This test is based on the idea that the greater the Hamming distance between two Iris Codes A and B is defined as

$$HD = \frac{\left\| (\text{code A} \otimes \text{code B}) \cap \text{mask A} \cap \text{mask B} \right\|}{\left\| \text{mask A} \cap \text{mask B} \right\|}.$$

The $\otimes$ operator is the Boolean XOR operation to detect disagreement between the pairs of phase code bits in the two Iris Codes (code A and code B), and mask A and B identify the values in each Iris Code that are not corrupted by artifacts such as eyelids/eyelashes and specularities. The $\cap$ operator is the Boolean AND operator. The $\|.\|$ operator is used to sum the number of “1” bits within its argument. The denominator ensures that only the phase-code bits that matter are included in the calculation, after any artifacts are discounted. In order to account for rotational inconsistencies, when the Hamming distance for two templates is calculated, one template is shifted left and right bit wise and a number of Hamming distance values are calculated from successive shifts [2]. This method corrects for misalignments in the normalized iris pattern caused by rotational differences during imaging. From the calculated distance values, the lowest one is taken. This serves as a measure of recognition performance, as it is the fractional Hamming distance that determines if identification has been made. The decision of whether these two images belong to the same person depends upon the following result [2].

- If HD = 0 decide that it is a perfect match between two iris codes
- If HD $\leq$ 0.32 decide that it is same iris
- If HD > 0.32 decide that it is different iris

Hamming distance of $\leq$ 0.32 allows identification with high confidence and used as a threshold for recognition.

B. Modified Normalized Euclidean Distance (NED)

Matching is based on Euclidean Distance between input feature vector and feature vectors in database.

$$\text{Modified NED} = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\frac{(CodeA\ (i) - CodeB\ (i))^2}{SD^{\ i}}}$$

N represents the width of the iris; Code A and Code B are input image feature vector and all the images codes in database respectively. That is, the input image's code is compared with all other iris codes that are stored in the database. The matching score is the minimum of these ED of all classes.

C. Modified Average Euclidean Distance (AED)

We use average Euclidean Distance classifier to recognize iris. The features of an unknown testing iris are compared with those of a set of know iris.

$$\text{Modified AED} = \frac{1}{M}\sum_{i=1}^{M}\sqrt{\sum_{j=1}^{N}\frac{(CodeA\ - CodeB\ )^2}{N}}$$

N represents the width of the iris and M represents number of coordinates in the outer circle of the iris. To derive the performance results, each original iris image was compared against ever other image in the database using the template matching technique.

Experimental Results

In this section, the numbers of experiments were performed in order to evaluate the performance of the methods using Matlab 7.0 on an Intel Pentium IV 3.0GHz processor with 512MB memory.

MMU Database

Experiments are conducted on MMU1 iris database [8] and 135 images are chosen for the experiments. Those 135 images are divided into 27 classes and each of them has 5 images. The first image from each class is selected to be the template. The remaining 4 images of each class are adopted as the test set.

Recognition Analysis

A. Hamming Distance

Figure 2 shows statistical distribution of Hamming distance between different and same iris feature vectors for both compressed and uncompressed iris. The y-axis and x-axis indicate the number of data samples and the Hamming distance respectively. It indicates that the Hamming distance is between 0.16 and 0.32 for the iris images from the same eye and between 0.33 and 0.55 for the iris images from different eyes.

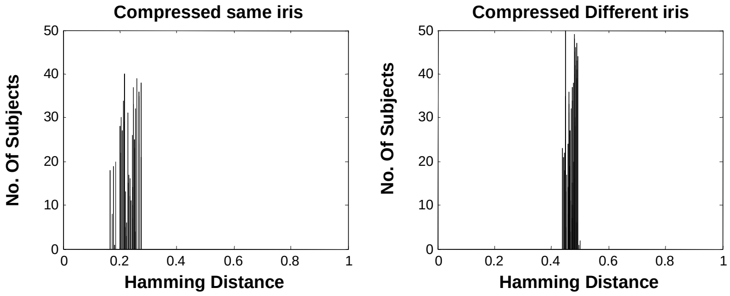

Figure 2(a): The distribution of Hamming distance for Compressed iris.

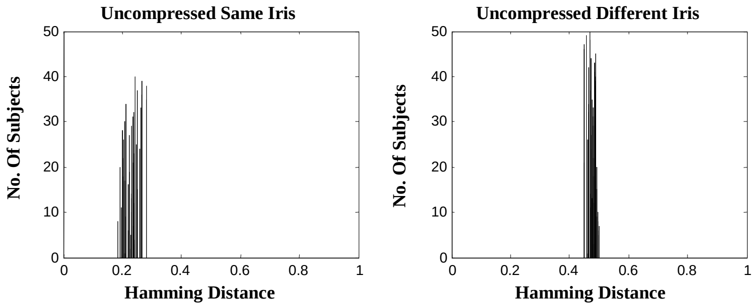

Figure 2(b): The distribution of Hamming distance for uncompressed iris.

In identification mode, the algorithm is measured by correct recognition rate (CRR), the ratio of the number of samples being correctly classified to the total number of test samples. The method of performance is evaluated using different distance measure as present in Table 1. The correct recognition rate of this system is 96% when we use 27 classes (135 images) [17]. The graphical representation in Figure 3 shows the recognition rate according to the Hamming distance.

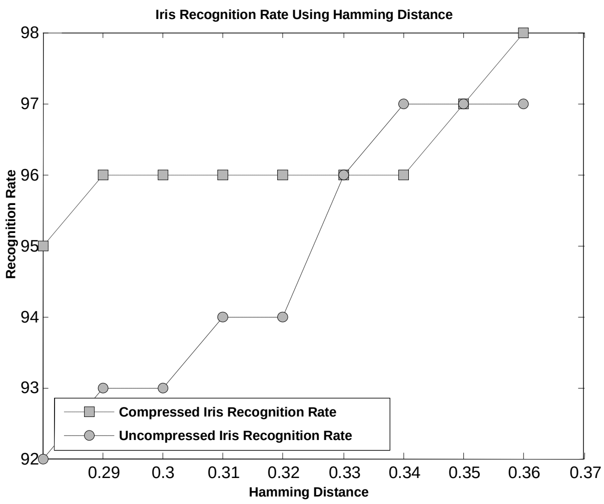

Figure 3: Iris Recognition Rate using Hamming Distance.

The average execution time for inner boundary detection was 0.016s, 0.031s for outer boundary detection and for matching was 0.016s using Matlab 7. Figure 4(a) and 4(b) shows that the processing time of iris recognition is relatively lesser when compared to the existing method.

B. Modified Normalized Euclidean Distance (NED)

From the proposed experimental results, the decision of whether two images belong to the same person depends upon the following conditions.

- If NED = 0 decide that it is a perfect match between two iris
- If NED $\leq$ 5.0 decide that it is same iris
- If NED > 5.0 decide that it is different iris

C. Modified Average Euclidean Distance (AED)

The decision of whether these two images belong to the same person depends upon the following result.

- If AED = 0 decide that it is a perfect match between two iris
- If AED $\leq$ 0.135 decide that it is same iris
- If AED > 0.135 decide that it is different iris

The Correct Recognition Rate (CRR %) was computed as
CRR %=(Number of correct attempts) / (Total number of samples)
The False Acceptance Rate (FAR %) was computed as
FAR% = (Number of false matches) / (Number of imposter attempts)
The False Rejection Rate (FRR %) was computed as
FRR % = (Number of false rejections) / (Number of enrollee attempts).

Table 1: Results obtained using various distance measures.

Similarity Measure	Correct Recognition Rate	False Accept Rate	False Rejection Rate
Uncompressed Image using Hamming Distance	94%	0	0.11
Compressed Image Using A.Hamming Distance	96%	0	0.08
B.Modified Normalized Euclidean Distance	97%	0	0.07
C.Modified Average Euclidean Distance	97%	0.05	0.05

From the experimental results, the proposed methods show an overall accuracy of 96% and above.

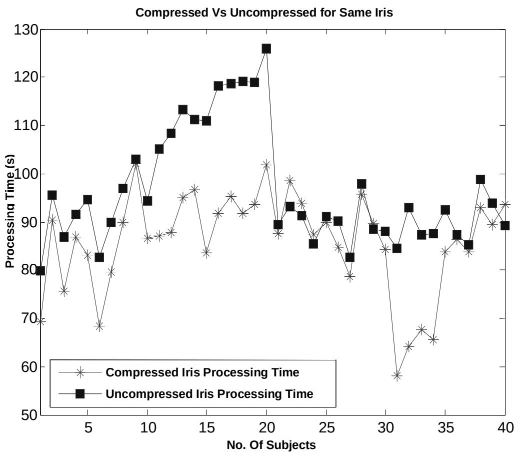

Figure 4(a): Processing Time of Compressed Vs Uncompressed for same Iris.

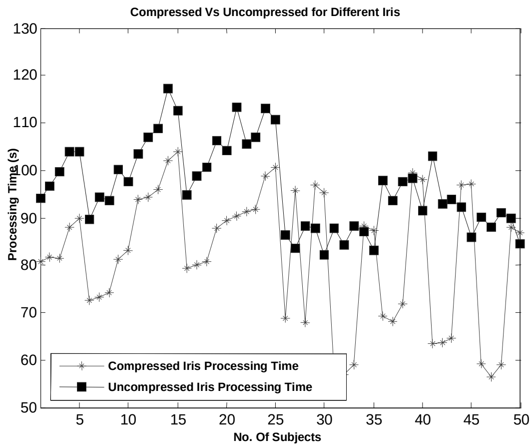

Figure 4(b): Processing Time of Compressed Vs Uncompressed for different Iris

Conclusion

Proposed iris recognition method is relatively simple and efficient against existing methods. We reached the correct segmentation for the pupil center and outer boundary radius and also average execution time for inner boundary detection was 0.016s, 0.031s for outer boundary detection and for matching was 0.016s using Matlab 7. From the experimental results, the Hamming Distance, Modified NED and Modified AED show an overall accuracy of 96% and more. The processing time of iris recognition is relatively lesser when compared to the existing method. The experimental results show that the proposed approaches have a good recognition performance and speed. This experiment is applicable to do experiments on a larger iris database in various environments for iris recognition system.

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