# Iris Recognition Using Non Filter-based Technique

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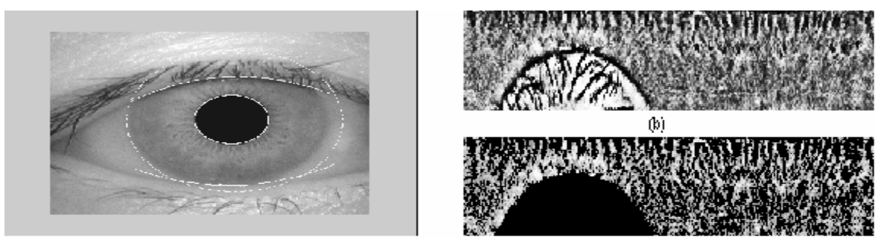
## 1. Introduction

The human iris, an annular part between the pupil and the white sclera is emerging as a highly reliable biometric trait for personal identification. Although the area of the iris is small it has enormous pattern variability which makes it unique for every person and hence leads to high reliability. Modern cameras that are used for acquiring iris are less intrusive compared to earlier iris scanning devices and public awareness of system reliability and difficulty to circumvent is developing. An iris recognition system has following sub systems: (1) Image acquisition, (2) Image preprocessing, (3) Texture Extraction, and (4) Decision Making. The texture extraction is the most important of all of these. We propose an iris texture extraction technique using the Grey Level Co-occurrence Matrix (GLCM). The proposed approach is a non filter based iris recognition technique and is invariant to iris rotation.

## 2. Methods

The designed system has been tested on the CASIA (The Chinese Academy of Sciences – Institute of Automation) database [1]. The dataset has 756 grayscale “non-ideal” eye images that come from 108 different users with 7 images per user. In many instances the images are occluded and defocused. On these images we applied the preprocessing steps of J. Daugman’s algorithm [2]. The preprocessing step includes:

1. Iris Localization: The sclera, pupil and eyelids are segmented (Fig 1(a)).
2. Iris Normalization: Transformation of localized iris region from Cartesian coordinates to Polar coordinates (Fig 1(b)).
3. Masking: The region corresponding to eyelids and eyelashes are then masked (Fig 1(c)).




(a) (c)

Fig. 1

In this research we focus on texture extraction from the normalized iris image. Instead of using Gabor filters [3], to extract the textural features from the image we propose the use of a non filter based technique that depends on second order statistics of the pixel intensities. The co-occurrence matrix estimates the joint probability distribution function of gray level pairs in an image. The technique uses the GLCM (Grey Level Co-occurrence Matrix) of an image and it provides a simple approach to capture the spatial relationship between two points in a texture pattern [4]. It is calculated from the normalized iris image using pixels as primary information. The GLCM is a square matrix of size G X G, where G is the number of gray levels in the image. Each element in the GLCM is an estimate of the joint probability of a pair of pixel intensities in predetermined relative positions in the image. The $(i , j)^{th}$ element of the matrix is generated by finding the probability that if the pixel location $(x , y)$ has gray level $I_i$ then the pixel location $(x+dx , y+dy)$ has a gray level intensity $I_j$. The dx and dy are defined by considering various scales and orientations.

The joint probability of co-occurrence of grey levels a and b for two pixels with a defined spatial relationship in an image is calculated (the spatial relationship is defined in terms of distance d and angle θ). In this work, the matrices are constructed at a distance of d=1, 3, 5 and 10 and at angles incremented from θ= -45° to 135°. Various textural features have been defined based on the work done by Haralick [4]. These features are derived by weighting each of the co-occurrence matrix values and then summing these weighted values to form the feature value. These weighting functions can be divided into two classes as shown in Fig 2:

1. Weighting based on element value.
2. Weighting based on spatial position.

For matching these features we used the 'Euclidean distance' as our criterion. The specific features considered in this research are defined as follows:

1) Energy: $f_1 = \sum_i \sum_j p(i, j)^2$

2) Contrast: $f_2 = \sum_{n=0}^{N_g - 1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i, j) \middle\| i - j \middle| = n \right\}$

3) Correlation: $f_3 = \dfrac{\sum_i \sum_j (ij)\, p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y}$

4) Homogeneity: $f_4 = \sum_i \sum_j \dfrac{1}{1 + (i - j)^2}\, p(i, j)$

5) Autocorrelation: $f_5 = \sum_i \sum_j (ij)\, p(i, j)$

6) Dissimilarity: $f_6 = \sum_i \sum_j |i - j| . p(i, j)$

7) Inertia: $f_7 = \sum_i \sum_j (i - j)^2\, p(i, j)$

here $\mu_x$, $\mu_y$, $\sigma_x$ and $\sigma_y$ are mean and

standard deviation along x and y axis

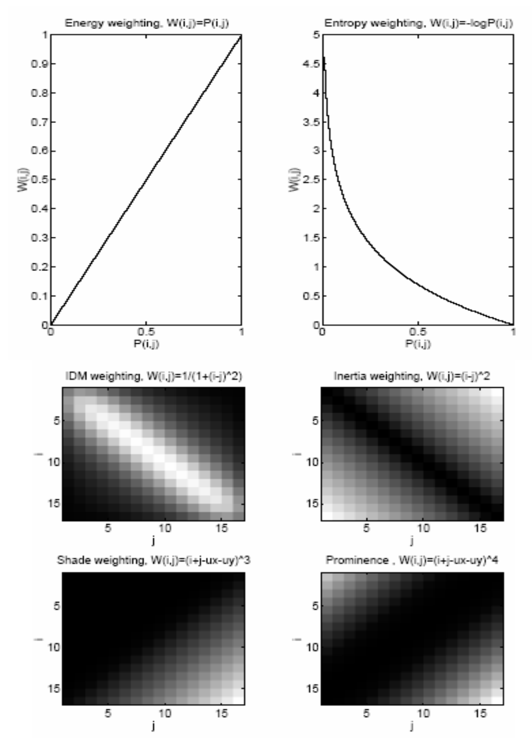



Fig. 2

**3. Results:**

Our new technique is found to have good performance characteristics in the sense it establishes that non filter based techniques can be successfully used for iris identification. It gives an EER of 9.32 % and a d-prime value of 1.632. The ROC curve (Fig 3) shown below summarizes the performance of the proposed technique. The technique described has an inherent advantage over any of the filter based technique in the sense that it is invariant to iris rotation. Because the co-occurrence matrices are constructed for many orientations, the rotation of the iris is captured by one of the matrix which is unlike any of the technique presently used. Images shown in Fig 4 are from the same user and one is rotated with respect to other, but still our technique gives low value of 'Euclidean distance' between the two.

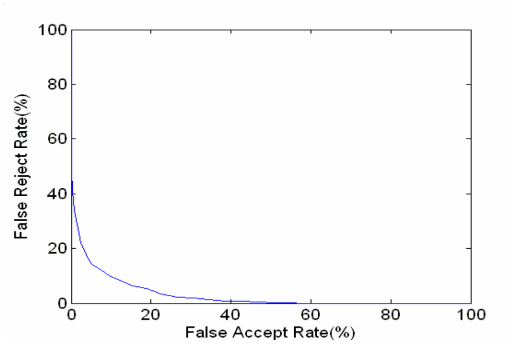
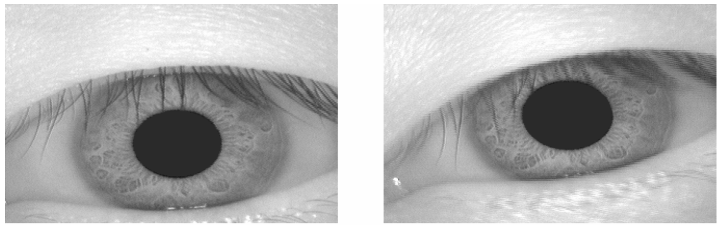



Fig 3. ROC



(a) (b)

Fig 4.

## 3. Conclusions and Improvements:

The GLCM proved to be a good technique as it provides reasonable accuracy and is invariant to iris rotation. By incorporating few modifications such as extracting texture information from a block (as opposed to a pixel), the performance of the technique can be improved. Furthermore more sophisticated feature selection technique than sequential forward search can be employed. Current work includes more comparison of this technique with filter based techniques in order to assess the benefits of the former.

## 7. References


1. CASIA Iris Image Database (ver. 1.0), http://www.sinobiometrics.com/casiairis.htm.
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