Iris Recognition Based on GLCM and FFT Feature Set Fusion

A. Alice Nithya\textsuperscript{1}, C. Lakshmi \textsuperscript{2} and R. Rani Krithiga\textsuperscript{3}
School of Computing, SRM University, Kattankulathur - 603 203, Tamil Nadu, INDIA.
a.alicenithya@gmail.com

February 10, 2017

Abstract

In this paper, both the spatial domain features and the frequency domain features of iris images are studied and used to design a hybrid feature extraction technique taking advantages of both the methods. A fused feature set obtained from Grey-Level Co-occurrence Matrix (GLCM) and Fast Fourier Transforms (FFT) are created. GLCM is a non-filter-based technique, used to extract information about both the distribution of pixel intensities as well as the relative position of neighborhood pixel values. FFT is used to extract the phase components and frequency domain magnitude information. This fused feature set helps to increase the overall system efficacy. Multi-class Support Vector Machines (SVM) is used for classification. Experimental results on CASIA iris dataset show that the overall system efficiency is improved by fusing the features with false rejection rate higher than false acceptance rate.

AMS Subject Classification: 62H35, 68U10, 68T10.

Key Words and Phrases: FFT, GLCM, Iris Recognition, Multi-class SVM...
1 Introduction

Identification, authorization, and accountability are the three main components of system security. An individual should be identified first to gain access into the system [1]. Biometric technologies are selected over traditional techniques for identifying an individual, as traditional techniques are more vulnerable and provide insufficient security, in today's highly connected and data-driven world [2]. Biometric technologies for security applications are based on any one or combination of the following identifiers: face, fingerprint, iris, voice, gait, DNA and so on [3]. Among these biometric identifiers, iris has gained more attention. Iris patterns due to its unique, stable and highly variable texture information are considered as a reliable identifier for personal identification. Though iris is small in size (11 mm) and difficult to acquire images, due to its huge variation in patterns, it provides great mathematical advantages [4].

The building blocks of an iris recognition system are as follows [5]: (i) Image Pre-processing, (ii) Feature Extraction and (iii) Matching. Among the three building blocks, by improving feature extraction techniques, powerful characteristic discrimination could be achieved at low cost with reduced feature dimensions. In this paper, we focus on the development of a novel feature extraction technique which provides good recognition rate with reduced feature vector size which takes advantages of both phase based and texture based features of iris images. Iris images acquired in near infrared illumination reveals texture information to a greater extent making texture analysis based feature techniques to provide higher recognition rate [6]. Similarly, FFT helps to identify normalized cross correlation which helps in finding the best match between any two images. Thus this research work helps to exploit the advantages of both spatial and frequency domain features and statistical modeling for texture-based feature analysis, extraction of features and creation of feature vectors in the context of iris-based biometric system.

The remainder of this paper is organized as follows: Section 2 introduces the experimental setup, the relative properties and working methodologies of GLCM and FFT for iris images and the statistical features extracted from them. Experimental results are analyzed and discussed in section 3. Section 4 concludes the paper.
2 Experimental Methodology

In this paper, since we focused on iris recognition stage of the entire iris biometric process, few of the common challenges of a complete iris biometric system, starting from image acquisition were bypassed, and eye images available in the publicly available CASIA dataset [7] were used for result analysis.

2.1 Image Pre-processing

The first step to be done with the iris image dataset was to identify the iris ROI, followed by normalizing the iris ROI for further processing. Iris ROI is localized by identifying the iris-sclera and iris-pupillary boundary using Circular Hough Transform (CHT) [8, 9]. Iris normalization stage was performed to transform the localized iris ROI identified into a fixed size matrix to account for the variations in iris sizes among different eye images [6]. Even for the same person due to variation in illumination, or pupil dilation effects, the size of the iris may vary. Annular iris ROI was then normalized to a uniform rectangular form by applying Daugmans rubber sheet method [10]. Steps involved in iris ROI localization are as follows:

1. Identify iris and pupil center and radius respectively, using CHT [8].
2. Define rectangular boundary using iris center and radius.
3. Threshold limit is set to top 10% of the pixel intensity values are set to identify and remove specular reflections [11].
4. Threshold limit is set to bottom 30% of the pixel intensity values to identify pupil, eyelids and eyelashes.
5. A black rectangular box of size [30 X diameter of iris] was created and mapped onto the upper and lower portion of the iris.
6. Each pixel in the iris ROI is mapped into a pair of the polar coordinate form (radial resolution, angular resolution), where radial (horizontal dimension) and angular (vertical dimension) resolution are in the intervals of [0 1] and [0 2π] respectively.
2.2 Feature Extraction

Features are used to represent an iris image; they could be either local or global or both local and global information about an iris. In this paper, we created a feature set with combined features obtained from texture based analysis and phase based methods. Texture based feature extraction is the process of analyzing the surface characteristics and appearance of an image and extracting the features required for representation. In phase based methods, like Fourier Transforms, geometric characteristics of a spatial domain, input image could be accessed. Though the area of the iris is small, pattern variability present in it is very enormous. This rich, unique and stable texture information present in iris made it reliable and easier to be processed using texture-based feature extraction techniques [12] as well as phase based feature extraction techniques [13] so that better accuracy rate could be achieved with reduced number of features. Proposed iris recognition framework is depicted in Figure 3.

2.2.1 Gray-Level Co-occurrence Matrix (GLCM)

GLCM [14] helps to analyze texture information of an iris image by finding the second order statistics properties. The GLCM is a table having entries as different combinations of pixel gray level occurrence based on relative orientation and relative distance in an image usually represented by $P(d, \theta)(i, j)$. Here the parameter $d$ defines the spatial relationship between pixel values in terms of distance, whereas $\theta$ defines it in terms of orientation. GLCM has fourteen features. Generally, the orientation parameter $\theta$ will be limited to $[0^\circ, 45^\circ, 90^\circ, 135^\circ]$ representing, horizontal scan, top-down diagonal scan, vertical scan and bottom-up diagonal scan respectively to account for rotational invariance. Similarly, $d$ is a varying parameter, based on which number of co-occurrence matrices could be increased for a given image and will normally be limited to smaller values ranging from $[1, 2, 3]$. By keeping smaller and suitable $d$ value, the recognition rate was increased and the computational time of the system was found to be decreased.

A series of second order texture calculations could be developed from the created GLCM [15]. There are nearly 14-second order statistical properties could be defined from the GLCMs created. In
this work, based on experimental trial and error, we have identified the following features to provide good recognition rate for iris images. They are as follows:

1. **Contrast** Sum of squares variances usually identified using the following equation

\[ f_1 = \sum_{i,j=1}^{N} P_{i,j}(i - j)^2 \quad (1) \]

2. **Correlation** Identifies the correlation between a pixel value to its neighbor over the entire image identified using the following formula

\[ f_2 = \sum_{i,j=1}^{N} P_{i,j}(i - \mu_i)(j - \mu_j)/\sigma_i\sigma_j \quad (2) \]

3. **Homogeneity or Inverse Difference Moment** Used to identify the closeness of the element distribution in GLCM to its diagonal.

\[ f_3 = \sum_{i,j=1}^{N} P_{i,j}/(1 + |i - j|) \quad (3) \]

4. **Energy** Sum of squared elements of GLCM

\[ f_4 = \sum_{i,j=1}^{N} P_{i,j}(i, j)^2 \quad (4) \]

5. **Dissimilarity** Unlike contrast the weights increase linearly here.

\[ f_5 = \sum_{i,j=1}^{N} |i - j|P_{i,j} \quad (5) \]

6. **Autocorrelation**

\[ f_6 = \sum_{i,j=1}^{N} (i, j)P_{i,j} \quad (6) \]

### 2.2.2 Fast Fourier Transform (FFT)

The Fourier Transform helps to decompose an input 2D image to its corresponding sine and cosine components. Each point in the spatial domain image is represented as frequencies in Fourier or
frequency domain. For an input image of size \([M \times N]\), FFT is given by:

\[
F(u, v) = \sum_{i,j=1}^{M,N} I(i,j) e^{-i \times 2\pi \left(\frac{ki}{M} + \frac{lj}{N}\right)}
\]  

(7)

Since Fourier transform decomposes an image into its sinusoidal components, it is easy to examine and process certain frequencies [13], thus influencing the geometric structure of an image. In this work, DC-value (image mean), \(f_7\) and AC-value, \(f_8\) are calculated and stored as features for further processing. By applying texture based and phase based methods, eight features say \(f_1, f_2, f_3, f_4, f_5, f_6, f_7,\) and \(f_8\) are obtained to represent the input iris image. Features created for individual iris images are stored in a database for matching.

2.3 Matching

Multi-class SVM could be used when there were more than two classes present in the input database. SVM works on supervised learning principal and by default is a binary classifier. However, it could be extended to perform one vs. all classification also. Matlabs in-build svmtrain and svmclassify functions are used to perform multi-class classification in this work.

3 EXPERIMENTAL RESULTS

The proposed algorithm was tested using non-ideal images taken from CASIA Iris-interval dataset [7]. This dataset has detailed texture information of iris images which helps to design novel feature extraction techniques. There are 2,639 images with 395 classes taken from 249 subjects of resolution 320*280. In this paper, results were tested on 20 classes with 80 images. It was tested using MATLAB R2015a. During enrollment phase, pre-processing and feature extraction processes were executed sequentially for individual iris images and the 6 features for GLCM and 2 features for FFT were extracted. Initially recognition rate was calculated for GLCM and then with combined features of GLCM and FFT.

GLCM features were extracted in \([0^\circ, 45^\circ, 90^\circ, 135^\circ]\) orientation set for the relative distance \(d= 4\) (for iris images recognition rate
is found to be improved when d = 4). For multi-class classification, i.e., one vs. All SVM was used. Table 1 shows the comparison of classification accuracy of GLCM and combination of GLCM with FFT. Figure 1 characterizes the performance analysis of the proposed algorithm based on classification accuracy and the number of classes.

![Performance Analysis of Proposed Algorithm](image-url)

Table 1: Comparison of Classification Accuracy

<table>
<thead>
<tr>
<th>No. of Classes</th>
<th>No. of Training data</th>
<th>No. of Testing data</th>
<th>FRR (GLCM)</th>
<th>FRR (GLCM+FFT)</th>
<th>Recognition Rate (GLCM)</th>
<th>Recognition Rate (GLCM+FFT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>82</td>
<td>20</td>
<td>4.88</td>
<td>2.44</td>
<td>75%</td>
<td>90%</td>
</tr>
</tbody>
</table>

Figure 1: Performance Analysis of Proposed Algorithm
4 Conclusion

Second-order statistical properties extracted from the GLCM obtained from iris images when combined with FFTs DC and AC-value, is proved to increase overall system efficiency. By creating GLCM for different orientations, this system provides rotational invariance also. From this work, it is observed that the classification accuracy of the system increases when the number of samples per classes increase or by combining features of GLCM with FFT. Classification accuracy for GLCM is 75%, and the same is 90% in proposed. By incorporating few modifications, different texture models can be fused as future work. More sophisticated feature selection techniques can be incorporated to improve system efficacy.

References


